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Stock Price Prediction in Sub-Saharan Africa

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Declaration of Authorship

I, Dennis MUREKACHIRO, declare that this thesis titled, "Stock Price Prediction in Sub-Saharan Africa" and the work presented in it are my own. I confirm that:

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- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
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Signed: D.Murekachiro

Date:29.11.2020

"The greatest challenge to any thinker is stating the problem in a way that will allow a solution."

Bertrand Russell

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Abstract

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Stock Price Prediction in Sub-Saharan Africa

by Dennis MUREKACHIRO

Investors, researchers and practitioners are continuously exploring various ways to understanding stock market price movements and the development of techniques that can assist them in accurately predicting the stock markets and improve on investment decision making and policy making. This study sought out to develop a prediction model for stock markets, determine which factors move stock prices and investigate the inefficiency of 11 selected stock markets. In order to predict the stock markets, this study made use of deep learning prediction models (LSTM, RNN, GRU, BLSTM, BRNN, BGRU) and statistical GAM in ten sub-Saharan African countries (Botswana, Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tunisia, Zambia, Zimbabwe) and the S&P500 (USA). Stock markets are predictable with inefficiencies found for the African stock markets as evidenced through calendar anomalies and high prediction accuracies whilst the lower prediction results for the S&P500 indicate market efficiency. The prediction model greatly improved prediction accuracy. However, there is no remarkable difference between unidirectional and bidirectional prediction models accuracy results for the eleven countries concerned. GAM statistical approach outperformed compared to all deep neural networks architectures in this study. The varying results for each country point to the uniqueness of each market confirming the varying market ecologies. In addition, this study also investigated the effect of macroeconomic variables (inflation, money supply, interest rates, exchange rates) on stock prices. Time series analyses were implemented through Johansen cointegration and Granger causality tests for short and long run relationships between macroeconomic variables and each stock market. Overall, empirical results for the African stock markets reveal a negative association between closing price and exchange rates, a positive relationship between money supply and closing stock prices for all countries. Mixed results for the other variables for each country attest to the fact that stock markets are unique and are influenced differently by these macroeconomic variables. Notably, African stock markets relate differently to macroeconomic variables as compared to developed stock markets. Stock market predictions were run on a python 3.5 environment using deep learning libraries Theano, Tensorflow, and Keras and Scikit learn and the time series analysis was analyzed using stata13 and R 3.6 software.
Keywords
Stock prices, African stock markets, Prediction, Deep neural networks, Macro-economic variables, decision making, GAM. .

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List of Abbreviations

ADF	**A**ugmented **D**ickey **F**uller
AMH	**A**daptive **M**arkets **H**ypothesis
ANN	**A**rtificial **N**eural **N**etworks
APT	**A**rbitrage **P**ricing **T**heory
ARCH	**A**utoregressive **C**onditional **H**eteroscedasticity
ARIMA	**A**utoregressive **I**ntegrated **M**oving **A**verage
ARMA	**A**utoregressive **M**oving **A**verage
BGRU	**B**idirectional **G**ated **R**ecurrent **U**nit
BLSTM	**B**idirectional **L**ong **S**hort **T**erm **M**emory
BRNN	**B**idirectional **R**ecurrent **N**eural **N**etwork
CAS	**C**omplex **A**daptive **S**ystems **T**heory
CNN	**C**onvolutional **N**eural **N**etwork
CPI	**C**onsumer **P**rice **I**ndex
DNN	**D**eep **N**eural **N**etworks
EMH	**E**fficient **M**arket **H**ypothesis
GAM	**G**eneralized **A**dditive **M**odels
GARCH	**G**eneralized **A**utoregressive **C**onditional **H**eteroscedasticity
GRU	**G**ated **R**ecurrent **U**nit
IFS	**I**nternational **F**inancial **S**tatistics
LSTM	**L**ong **S**hort **T**erm **M**emory
MAD	**M**ean **A**bsolute **D**eviation
MAE	**M**ean **A**bsolute **E**rror
MAPE	**M**ean **A**bsolute **P**ercentage **E**rror
MSE	**M**ean **S**quare **E**rror
PEH	**P**roxy **E**ffect **H**ypothesis
POCID	**P**oint of **C**hange in **D**irection
RMSE	**R**oot **M**ean **S**quare **E**rror
RNN	**R**ecurrent **N**eural **N**etwork
RWT	**R**andom **W**alk **T**heory
SVM	**S**upport **V**ector **M**achine

Dedicated To my wife, Joyline and my Children;
Anochengetaishe, Anodaishe and Anoshamisaishe

Chapter 1

Introduction

1.1 Introduction

The accurate prediction of stock price movements enables investors to make decisions on whether to take long or short-positions on the stock and thereby make profit (Chai et al., 2015). Predicting the stock market movement requires a model that can accurately predict future prices (Taran et al., 2015). The aim of this research is to determine the extent to which deep neural network architectures and generalized additive models can accurately predict the stock market movement to aid in financial and investment decision making and to determine the factors that underlie such movement.

1.2 Research Background

The role of stock market in the economy is to provide liquidity to financial asset owners (Almomen, 2016; Masoud, 2013), capital formation for economic growth (Sulong et al., 2018; Ngare and Nyamongo, 2014; Enisan and Olufisayo, 2009), hence acting as a barometer of economic performance (Dagar, 2014), and risk reduction by offering opportunities for risk diversification (Ezeoha et al., 2009). The presence of a well, efficient functioning stock market system aid in mobilisation of limited resources from the surplus units to deficit units, hence promoting the efficient allocation of resources and leading other economic sectors in their growth process.

Previous studies (eg. (Pasquale, 2006)) document a positive relationship between stock market and economic growth and argue that when stock market rises, investors have the motivation to spend more because they feel wealthier and as a result the economy expands. On the other side, if the stock prices go down, investors tend to spend less, so the economic growth decreases. The stock market can be regarded as a good measure to forecast future economic growth and explain some applications of financial literatures.

(Levine and Zervos, 1996)in their research on the linkages between stock markets and long-run economic growth using 41 countries from 1976 to 1993, provided evidence that stock market is positively and significantly correlated to future economic growth and capital accumulation. On the other hand, critics to these findings based their arguments on the evidences that positive correlation between stock market and economic growth could be easily captured in some emerging countries which are characterized by their boom stock markets and catching-up growth, but when it comes to developed countries, hardly does this relationship exist.

Stock market is not only important for economic development, but reasonably accurate prediction of stock market is important to investors for developing trading strategies and for hedging against potential market risks which enable speculators and arbitrageurs to profit by trading in stock index (Leung et al., 2000). In addition, successful forecasting of stock prices generates substantial monetary rewards (Wei, 2016; Gocken et al., 2016; Nayak et al., 2015) and is a very large and profitable area to pursue (Kim and Han, 2016). These economic rewards motivate researchers, investment professionals and average investors to continuously pursue such accomplishments (Oztekin et al., 2016; Wang et al., 2016; Reid et al., 2014; Hsu, 2013; Liang et al., 2011; Lawrence, 1997).

However, the task of predicting stock market is challenging because of multiple, non-predictable factors that impact on the stock market such as natural disasters, political instabilities, varying economic climates, etc. In addition, the prediction of the stock market is made even more difficult by the fact that stock markets are complex, evolutionary and nonlinear dynamical systems. Furthermore, the forecasting of stock market is characterized by data intensity, noise, non-stationarity, high uncertainty, hidden relationships, deterministically chaotic data, randomness, volatility, irregularity and seasonality (Shan et al., 2015; Sanjeev, 2015; Liu and Hu, 2013; Kazem et al., 2013; Lu, 2013; Hsu, 2013; Wong and Versace, 2012; Araujo, 2012; Mohapatra et al., 2012; Araujo, 2010; Mostafa and Atiya, 1996; Hall, 1994). All the aforementioned characteristics of the stock market make its prediction challenging for most investors, asset managers and academia (Zhong and Enke, 2017; Anish and Majhi, 2016; Shan et al., 2015).

An attempt to predicting the stock market contradicts the long standing finance theories of Efficient Market Hypothesis (EMH) and Random Walk Theory (RWT). EMH states that stocks are informationally efficient, implying that it is impossible to predict the direction of the stock market based on the trading data. EMH can be explained by weak form, semi-strong form and strong form. The weak form market efficiency states that no one can utilize public information to acquire higher returns other than the return that is adjusted via market risk. This argument implies that no one can beat the market (Zhang et al., 2017b) and there is no possibility of economic profits (Plastun et al., 2020). In general, EMH argues that no amount of information would be useful in helping one to make predictions about an asset's returns (Chu et al., 2019).

The RWH is directly consistent with the EMH in that it assumes that stock prices resemble a random walk process where innovation to the prices is permanent. This implies that stock prices change randomly and that market prediction based on past return history of prices is difficult (Lawal et al., 2017; Oztekin et al., 2016). Stock prices move entirely in a random and unpredictable manner with every price change happening without any influence from past prices (Patel and Marwala, 2006) but only through new information or news (Gyamerah et al., 2019; Cavalcante et al., 2016). In other words, successive price changes are independent and identically distributed (Oztekin et al., 2016). Stock prices are independent of one another and this assumption is valid as long as information of the past behaviour of price series changes cannot be used to increase expected gains (Agwuegbo et al., 2010). RWT therefore purports that price changes have no memory and the past cannot be used to predict future prices effectively (Cavalcante et al., 2016).

In contrast to EMH and RWH, there is also a large body of literature that demonstrate that the stock market is actually inefficient and with appropriate tools and timing of the stock market, investors can predict the stock market and yield abnormal returns Patel et al. (2015b). Market inefficiency is exhibited through the existence of calendar anomalies in stock markets (Al-Khazali and Mirzaei, 2017). Investors and traders, who generate their trading strategies based on the identified calendar anomalies in a pursuit to increase returns, attain abnormal profits (Norvaisiene et al., 2015). In other words, calendar effects or anomalies are amongst prominent reasons for the occurrences of abnormal returns (Zhang et al., 2017b).

Evidence from the US market which was tested for the January effect, December effect and Mark Twain effect inefficiencies revealed that the January effect was the most outstanding one and produced opportunities for market participants to profit (Plastun et al., 2020). It was also found that US stock market short sellers use well-known equity anomalies in their shorting strategies by using short arbitraging strategy to exploit potential overpricing and short avoidance strategy to stay away from underpriced firms (Wu and Zhang, 2019). Focusing on the Islamic markets, (Wasiuzzaman, 2018) discovered that religious sentiment is important in influencing return and volatility of the Saudi stock market during the Hajj pilgrimage with low returns and high volatility during this cultural/religious anomaly.

The presence of calendar anomalies in the Gulf Cooperation Council affords money managers with a chance to optimally time their trades based on daily and monthly price fluctuations (Ariss et al., 2011). In another study, it was found out that 27 out of 167 equity anomalies studied for Islamic stocks were found to profitable (Zaremba et al., 2018). Further evidence of exploitable day of the week calendar anomalies for maximising investment return are noticed in 28 indices of stock markets in 25 countries studied by Zhang et al. (2017b). In addition to empirical evidence from use of the calendar anomalies to evidence stock market inefficiency, there is also a vast body of literature that defies the EMH and RWT by revealing different useful prediction initiatives to gain substantial gains. These are performed either through fundamental analysis, technical analysis, time series and machine learning methods or a combination of the four categories (Gocken et al., 2016; Ghezelbash and Keynia, 2014).

Fundamental analysis is useful for long term prediction (Sreelekshmy et al., 2017) by using global economic, industrial and business indicators to determine intrinsic value of a company's stock (Cervello-Royo et al., 2015). It is based on the principal that the market value of a stock tends to move towards its real value or intrinsic value (Qian and Gao, 2017). Thus, fundamental analysis mainly focuses on the listed firm operations, conditions and financial status in an effort to determine the intrinsic value of a firm's stock and forecast the future profits (Chen and Wang, 2015). In other words, fundamental analysis attempts to make predictions based on data regarding the structure of the economy i.e. inflation rates, trading volumes, interest rates, unemployment percentages, demands for the company products (Gunduz and Cataltepe, 2015) or simply it studies the economic factors that may influence market movements (Cavalcante et al., 2016).

Though macroeconomics data has significant influence on stock returns by possessing a significant impact on the growth and earnings prospects of the underlying firms (Tsai and Hsiao, 2010), fundamental analysis has a limitation in that the macroeconomic data or factors used are subjective (Cavalcante et al., 2016). Choosing economic factors that can be used as indicators of other variables future behaviour requires understanding of the delayed influences of relationships between many variables since many factors interact with the stock market. Thus attempts to pick the most influencing economic factors are not easy for fundamentalists (Oliveira et al., 2013). To avoid such subjectivity, this current work will focus more on machine learning algorithms that can mine data for key influencing variables.

On the other hand, technical analysis which is founded on the principles of the Dow Theory is useful for short term predictions (daily, weekly or monthly) by using historical prices to predict the future prices (Gunduz and Cataltepe, 2015) under the assumption that past behaviours have an effect on the future evolution of prices (Cervello-Royo et al., 2015). Technicians often model the historical behaviour of a financial asset as a time series with the belief that history tends to repeat itself (Cavalcante et al., 2016). Technical analysis, also known as charting believes that trends and patterns of an investment instrument's price, volume, breadth and trading activities reflect most of the relevant market information that a decision maker can utilise to determine its value (Tsai and Hsiao, 2010). It has been found to be more profitable to take trading decision using a combination of technical analysis with computational intelligence tools (Dash and Dash, 2016; Hu et al., 2015; Hsu, 2013; Dai et al., 2012; Texeira and Oloveira, 2010). With great computational power, researchers can use computational intelligent systems alone to make useful predictions, such as is implemented in this current research. Smarter intelligent systems that require less human intervention in choice of technical variables but can pick on its own the relevant prediction factor inputs are needed.

The prediction of time series models with traditional methods is an attempt to design linear prediction models (univariate models and multivariate regression models) to track patterns in historical data (Oliveira et al., 2013). Vast linear models such as autoregressive moving average (ARMA), autoregressive integrated moving average model (ARIMA) and nonlinear traditional time series models such as autoregressive conditional heteroscedasticity model (ARCH) and generalised ARCH (GARCH) have been proposed and applied to economic forecasting (Wei, 2016). Although these models have been vastly used, if data is from economic or financial factors, it is difficult to expect reasonable prediction performance because of reciprocal and complex influences among the factors (Park and Shin, 2016). Financial time series are essentially complex, highly noisy, dynamic, nonlinear, nonparametric and chaotic in nature (Cavalcante et al., 2016). It is on this premise that this current research will adopt machine learning models in order to capture the complex dynamics of stock markets.

Machine learning is a vibrant subfield of computer science that draws on models and methods from statistics, algorithms, computational complexity, artificial intelligence, control theory, and a variety of other disciplines. Its primary focus is on computationally and informationally efficient algorithms for inferring good predictive models from large data sets, and thus is a natural candidate for application to problems arising in high frequency trading, both for trade execution and the generation of alpha or excess returns (Kearns and Nevmyvaka, 2013). Machine learning methods use a set of data samples to draw (linear or nonlinear) patterns so as to approximate the underlying function which generates the data (Oliveira et al., 2013). Machine learning techniques have been applied with relative success in modelling and predicting financial time series (Cavalcante et al., 2016). It is the intent of this research to design a prediction model that increases prediction accuracy of machine learning techniques.

There are different machine learning techniques that have been applied for stock market predictions such as support vector machines (SVM)- (Kumar, 2016; Zhang et al., 2016; Chen and Lee, 2015; Fenghua et al., 2014; Luo and Chen, 2013; Lee, 2009); artificial neural networks (Persio and Honchar, 2016; Bisoi and Dash, 2014; Ruxanda and Badea, 2014; Liang et al., 2011); ensemble methods (Mabu et al., 2015; Ma et al., 2015; Kourentzes et al., 2014)and genetic programming (Hsu, 2011; Chen et al., 2009). The most used amongst these are SVMs and ANNs or their combination with other algorithms.In most cases, the machine learning approaches to stock prediction attempt to address portfolio optimization, investment strategy determination and market risk analysis initiatives(Liang et al., 2011). To this end, a number of different stock price prediction initiatives has been noted.

Founded on the structural risk minimisation principle and statistical learning theory, the SVM is one of the most effective machine learning algorithms for classification problems (Zhang et al., 2016). The basic idea of SVM is data transformation into a higher dimensional space and finds a classification hyper-plane that separates the data with the maximum margin. (Kumar et al., 2016) apply a proximal SVM to 12 market indices[1] and found out that the highest testing accuracy for 9 out of 12 stock indices considered in this study were achieved by the Random Forest- proximal SVM model. The highest accuracy was 62.72% for CNX Nifty.

In another experiment, (Luo and Chen, 2013) integrated a piecewise linear representation and weighted SVM (PLR-WSVM) for stock trading signal prediction for the Shanghai stock exchange in China. In comparison to other models, the PLR-WSVM performed better with highest accuracies for downtrend, steady trend and uptrend being 44.50%, 39.04% and 44.56% respectively. By combining SVM to a hybrid feature selection tool named F-score and supported sequential forward search (F_SSFS). (Lee, 2009) attained an average accuracy ranging from 85.5% to 88.5% for the NASDAQ stock market whilst (Fenghua et al., 2014) achieved a 67.98% directional symmetry for the Shanghai Stock exchange using singular spectrum analysis-SVM hybrid model. All these experiments are focusing on stock market trend classification. A consideration of stock market trend direction together with the absolute price prediction is ideal, a gap this current research focuses on with the intention to increase prediction accuracy from the low accuracies achieved by SVM related models.

Artificial neural networks (ANNs) and their variants have largely been used for stock price prediction (Persio and Honchar, 2016; Peace et al., 2015; Ruxanda and Badea, 2014; Xi et al., 2014; Bisoi and Dash, 2014; Liang et al., 2011). Artificial Neural networks mimic the human brain, its nervous system and the human's brain ability to classify patterns to make predictions based on past experiences (Karymshakov and Abdykaparov, 2012). In other words, neural networks are massively parallel systems comprising highly interconnected, interacting processing elements (neurons) that are based on neurological models. A key limitation of neural networks is that knowledge is not stored within individual processing units but is represented by the weight between units (Lu, 2010).

A procedural artificial neural network (PNN) was compared to back propagation neural networks, hidden markov model and SVM for yahoo stocks and it was found out that the space first PNN outperformed other model and attained a hit rate or accuracy of 68.9% (Liang et al., 2011) in correctly predicting the next day's actual price. ANNs were also used to forecast the Istanbul stock exchange and attained average accuracies of 70% (Karymshakov and Abdykaparov, 2012). (Ghezelbash and Keynia, 2014) designed an ANN to predict the Tehran stock exchange and attained 58.02% prediction accuracy. If simple ANN models could attain such prediction accuracy levels, a noble task to focus on would be to determine if prediction accuracy increases with the use of knowledge or memory retention models for stock prediction, a gap this current research attempted to address.

Notably, there is a growing consensus that model combination has advantages over selecting a single model in terms of accuracy and error variability (Kourentzes et al., 2014). An ensemble is a pool of base learners whose outputs are mediated by a pre-defined rule (Joao et al., 2014). In other words, ensemble learning is where several classifiers are created and the overall classification is done by combining

[1] S&P BSE Sensex (India), DAX (Germany), Hang Seng (Hong Kong), Jakarta Composite (Jakarta), KLSE Composite (Korea), Euronext 100 (Europe), CNX Nifty (India), Nikkei 225(Japan), NYA Composite (USA), Russell 3000(USA), Straits Times (Singapore) and Taiwan Weighted (Taiwan).

results generated by the classifiers (Mabu et al., 2015). The combination is able to complement the errors made by the individual classifiers on different parts of the input space (Tsai et al., 2011). (Chen et al., 2007) implemented flexible neural tree ensembles to NASDAQ and S&P CNX Nifty while (Tsai et al., 2011)predicted stock returns by classifier ensembles for the Taiwan stock market.The aim of (Tsai et al., 2011) study was to investigate the prediction performance that utilizes the classifier ensembles to analyse stock returns. Average accuracy for homogenous MLP classifier ensembles and heterogeneous classifier ensembles was 65.8% and 66.63% respectively for Taiwan stock market. Single classifiers attained average accuracy of 61.58%. From theses results, it is shown that classifier ensembles perform better than single classifiers do. In addition, (Ma et al., 2015) used tank based ensemble pruning for financial time series using the Dow Jones Industrial Average, Glaxo-Smithkline, Hangsen Index and Johnson Outdoors indices with point of change in direction (POCID) accuracies of 58.73%, 54.81%,69.02% and 59.34% respectively. Despite combining classifiers as one of the prediction models , relative success was achieved by the ensemble methods. Therefore, a search for other models that can increase prediction accuracy is essential.

In a study by (Nayak et al., 2016), a stock prediction model that combines historical prices and financial news sentiments was implemented to predict stock market trend and attained a prediction accuracy of 70% in the Indian stock market. In consideration of the work by (Bhardwaj et al., 2015) in using sentiment analysis for the Indian stock markets of Sensex and Nifty, the study demonstrated that sentiment analysis can be used for stock price prediction,analysing stock market conditions and for investment strategy determination. However, the paper does not report on accuracy levels or performance as measured by error metrics. (Smailovic et al., 2014) implemented a stream bases active learning for sentiment analysis in the financial domain which was combined to a SVM sentiment classifier. Owing to the fact that there are no publicly available large hand-labeled data for sentiment analysis of twitter data, the authors resorted to a Stanford university tweets database.

In another study, (Nguyen et al., 2015) performed sentiment analysis for 18 US market stocks from Yahoo finance and achieved a best result of 54.41 % accuracy level. The goal of (Nguyen et al., 2015) study was building a prediction model to predict the stock price movements (up or down) using the sentiment from social media. (Li et al., 2014) performed sentiment analysis on the Hong Kong stock exchange and attained prediction accuracies ranging from 18% to 69% for the utility stocks predicted. Two key issues regards sentiment analysis are availability of tweets which are beyond the reach of many, hence very few applications have been done in this area. Secondly, for studies on sentiment analysis for stock price prediction, relative success has been achieved with highest accuracy of 70%. The inclusion of news as input variables has not yielded better results as compared to other historical prices based models.

A more recent technique of machine learning in stock price prediction is deep learning. (Minh et al., 2018) implemented a deep learning approach for stock trend prediction based on a two stream gated recurrent unit work using both financial news and sentiment dictionary and attained a prediction accuracy of 66.32% for the S&P500. The TGRU stock trend prediction model used in this study outperformed GRU and LSTM models.Focusing on the same market, the S&P500, prediction accuracies based on alpha values and beta values of 62.27% and 65.08% were achieved respectively (Oncharoen and Vateekul, 2018). Focusing on the Taiwan stock exchange, (Gao et al., 2018) implemented a share price trend prediction model using convolutional recurrent neural networks combined with the long term short memory model

(ConvLSTM) and achieved an average error rate of 3.449 RMSE. Results were better as compared to the LSTM alone. In another experiment for the Taiwan stock exchange, the least RMSE error rate of 0.76 for Iron and Steel stock was achieved through use of LSTM in comparison to 8 other stocks in the same market.

An accuracy of 59% was achieved using the LSTM for the Ibovespa index from the BM&F Bovespa stock exchange. In addition, three learning architectures namely recurrent neural network (RNN), LSTM and CNN were compared against the ARIMA for stocks from the Nifty index in India. Results revealed that deep learning models outperformed the ARIMA model in stock prediction for the Indian stock market. A need to ascertain if deep learning models superiority over statistical models holds for African emerging and frontier markets is crucial, a gap that this current research focused on. (Chen et al., 2015) also implemented the LSTM model for Shangai and Shenzen indices in China and managed to improve prediction accuracy from 14.3% to 27.2% from the alternative methods compared to the LSTM. Most of DNN implementations took a comparative approach of models for the same market and failed to explain why the models perform differently in their discussion of results. In addition, only a few DNN models i.e. RNN, LSTM, CNN and GRU were implemented for stock price prediction. The bidirectional architectures of these models were not explored in stock price prediction, a dimension that this current study focuses on.

African stock markets have also been predicted using various techniques including some of the previously mentioned models. Traditional time series models such as ARIMA and GARCH have been extensively applied for the Nigerian stock market. (Adebiyi et al., 2014)implemented stock price prediction using the ARIMA model for the Nigerian stock exchange and New York stock exchange. After several experiments, the best ARIMA model for zenith bank index was 1, 0, 1 and for nokia was (2, 1, 0) with adjusted R^2 of 0.9972 and 0.0033 respectively. The Nigerian stock exchange was inefficient whilst the US market proved to be efficient. Though the R^2 of Zenith bank was high, an increasing deviation of predicted values from actual values was noticeable over the one month-ahead prediction, hence making the results questionable.

In another study, (Olayiwola et al., 2016) determined that an ARIMA (1, 1, 2) was successful in predicting stock returns of the All share index of the Nigeria stock exchange. Contrasting results on ARIMA's ability to estimate the Nigerian all share index were found by (Isenah and Olubusoye, 2014) who implemented two artificial neural network based models (tech 4-3-1 and tech 3-3-1) and compared them to a baseline ARIMA (3,0,1) model in predicting the Nigerian stock exchange. The neural networks and ARIMA had directional accuracies of 45.45%, 45.45% and 27.27% respectively. A need to develop a better prediction model(s) is essential as results show that both ANNs and ARIMA failed to predict the Nigerian All share index.

(Ajao and Wemambu, 2012) implemented an ARCH to estimate return and volatility prediction for the Nigerian stock market. Experimental results showed that about 67%, 77%, 56% and 65% of the systematic variations in Mobil, First Bank, Nigeria brewery and Nestle stock prices respectively are explained by past stock prices and stock price volatility. (Ibrahim, 2017)also found ARCH models ((ARCH (1); GARCH (1,1);TARCH (1,1); EGARCH(1,1) and PGARCH(1,1)) to be efficient whilst ARIMA was not efficient in developing volatility models for the Nigerian stock exchange. ARIMA models (3,1,3; 1,1,3 and 3,1,1) implemented in the experiment suffered from autocorrelation and ARIMA models (3,1,3; 1,1,3; 3,1,1; 2,1,2; 2,1,3 and 3,1,2) suffered from heteroscedasticity and were not normally distributed, rendering all the ARIMA models implemented unreliable and not efficient to estimate the forecast of the Nigerian All share index. EGARCH (1,1) was found to be most efficient method out of all the estimated ARCH family models as it has the least Akaike information criterion (AIC) and Schwarz information criterion (SIC). In another study, the GARCH (1,1) model was determined to be the best model to explain stock return volatility in Nigeria (Emenike, 2010). The ARCH family models are better predictors of the Nigerian All share index. However, there exists a need to compare ARCH prediction performance with other prediction models, especially intelligent machine learning models due to their better learning and adaption ability.

Taking a different approach, (Okoro, 2017)implemented fundamental analysis by investigating the effect of macroeconomic factors on the Nigerian stock exchange performance. An R^2 of 27.8 was attained implying that the macroeconomic factors used (gross domestic products, money supply, interest rate, inflation rate and exchange rate) cannot be used to predict performance of the Nigerian stock exchange. In another study by (Ajekwe and Ibiamke, 2018) used financial statement analysis to predict stock returns of listed consumer goods in Nigeria. About 34.4% to 46.7% variations in the equity returns according to the R^2 were found predictable through a combination of 14 accounting ratios using a univariate logit regression model. When using a multivariate logit equity returns regression model, financial statement analysis was able to predict accurately stock returns by 76.6%. The key limitation of this study was use of a small sample of 111 observations only in contrast to other studies that used more than 11 000 observations (Ou and Penman, 1989).

With regards to technical analysis prediction of African stock markets, (Dotti, 2016) focused on the profitability of technical trading rules based on ANN for the Kenyan stock market. The Nairobi stock exchange 20 index was used for this study owing to data availability. The percentage of correctly predicted signs for the bear market, stable market and bull market were 50%, 60% and 42% respectively. A need to develop better prediction models is essential. In addition, comparative studies using the same technical trading rules based on ANN for other African stock exchanges are necessary in order to test usefulness of the model.

Notably, the bulk of prediction initiatives for African markets are implemented through various machine learning models. (Berradi and Lazaar, 2019)implemented an integration of principal component analysis with recurrent neural networks to forecast the stock price of Casablanca stock exchange. The mean square error of the test data was 0.00596 compared to 0.011835 without use of principal component analysis. Using a fuzzy-neural intelligent trading model for stock price prediction, (Umoh and Inyang, 2009) obtained a 78% certainty that there will be a rise in stock prices for the Nigerian stock exchange. An MSE of 0.222 was attained for this experiment. In another experiment that used a rough set theory predictive model for Johannesburg stock exchange, (Khoza and Marwala, 2011) achieved an accuracy of 80.4% using a standard voting classifier.

(Quahilal et al., 2016) optimised stock market prediction for the Moroccan stock exchange by using a hybrid approach based on Hodrick-Prescott filter and support vector regression. The Maroc Telecom financial time series was used and results show that the SVR-HP model had the best mean absolute percentage error. In another study, (Akinwale et al., 2009) implemented error back propagation ANNs for predicting the Nigerian stock exchange and attained prediction accuracies of 11.3% and 2.7% on translated and untranslated Nigerian stock market prices.

Also focusing on the Nigerian stock exchange, (Kareem and Adeoti, 2016) used discriminant analysis and ANN to predicting the Nigerian stock market. Discriminant analysis was able to classify with 29.6% classification accuracy while the ANN posted a 72.2% accuracy level. In another experiment, (Patel and Marwala, 2006) attempted to forecast the Dow Jones Industrial Average (DJIA), Johannesburg Stock

Exchange All Share, NASDAQ 100 and the Nikkei 225 Stock Average indices using neural networks. The highest prediction for JSE All Share was 67.5%. In addition, the use of GARCH family models with ANNs has also been extended to the Moroccan stock market (Elbousty et al., 2019). The results point to the efficiency of neural networks in enhancing the performance of GARCH models.

(Mohamudally-Boolaky et al., 2019) implemented a support vector machine for predicting the Stock Exchange of Mauritius. The results obtained for this study showed that percentage accuracy ranged in between 60% and 70%. In another experiment for the Moroccan stock market, (Labiad et al., 2016), developed a short term prediction framework to forecast the Moroccan stock market. Up and down future trends of the market on a 10 to 60 minutes ahead basis were done using MLP and LSTM. The MLP had an average precision of 65% whilst the LSTM had an average 74% precision. In another experiment, (Gyamerah et al., 2019) implemented a stock price model using stacking ensemble learning method on the Nairobi stock exchange. The stacking ensemble learning method which used two base learners (Adaptive boosting and KNearest neighbours) and a gradient boosting machine as the meta-classifier outperformed the two individual classifiers. Accuracy levels were at 78.1% and had a kappa of 55.16%.

From the preceding cited studies, it can be concluded that African markets are inefficient and predictable though there are inconclusive author perspectives on the matter for certain African stock exchanges. For example, (Lawal et al., 2017) found the Nigerian stock exchange to be inefficient as shown from results of the Morlet's wavelet analysis which reject the random walk for all Nigerian All share stock exchange index. Thus arbitrage opportunities exist in the Nigerian stock exchange. However for the same market, (Agwuegbo et al., 2010) found out that the Nigerian stock exchange follows a random walk. Investment strategies based on past information were found not to yield to higher returns as price formation is believed to be a stochastic process. This study shows that stock price changes have no memory of the past history and purport that stock prices in Nigeria is a martingale. In other words, knowledge about the past is of no use in predicting future stock prices owing to the fact that prices are random.

In consideration of the afore-mentioned literature, first,it can be noted that several prediction approaches have been implemented for portfolio optimization, investment strategy determination and stock market risk analysis. However, most of the initiatives were directed towards trend prediction and a need to come up with absolute stock price prediction models remains a necessity. Second,other key questions still need to be addressed. Are African markets inefficient and predictable? Is there potential of increasing prediction accuracy for African stock exchanges? Can better prediction models be developed for emerging and frontier African stock exchanges in spite of the fact that most markets are illiquid, volatile, inefficient, are faced with narrowness of the markets (Mustapha and Ahmed, 2019; Mohamudally-Boolaky et al., 2019; Lawal et al., 2017).

1.3 Research Problem

Ideally, stock price prediction models should simulate real stock markets and aid portfolio holders to effectively manage their financial resources and maximize returns. Successful prediction of the stock market addresses a key challenge of financial decision making under uncertainty in modern finance and leads to the attainment of substantial monetary rewards (Nayak et al., 2015). Successful prediction initiatives with prediction accuracies closer to or equal to 100% are the most desirable. They provide pathways for investors to take proactive and knowledge driven decisions in order to achieve successful gain with less investment risk (Dash and Dash, 2016). Investment risk is reduced by selecting the type of securities for investment, the amount for investment and the timing of the investment using information from the prediction process (Zahedi and Rounaghi, 2015). However, ongoing attempts to predict stock market prices have been made difficult by the problem of increasing complexity of stock markets marked by increasing nonlinearity and evolutionary dynamism (Lo, 2004).

Although there is a vast amount of literature on ARIMA and ARCH models in the prediction of African stock markets, a heavy concentration is on the Nigerian stock exchange with the following studies (Adebiyi et al., 2014; Isenah and Olubusoye, 2014; Ajao and Wemambu, 2012)amongst many. Results generalisations cannot be done for other African stock exchanges. Statistical or time series prediction models such as ARIMA have failed to accurately predict stock markets and support maximization of investor returns due to two reasons. One, ARIMA models are limited in time series prediction because of their linearity characteristic which fails to predict most real-world problems which are nonlinear in nature (Araujo, 2010) like the stock market and for lack of long term temporal dependencies in their prediction. Two, ARIMA models and their variants are infrequently used for prediction initiatives because of their high computation costs. These models are unlikely to predict the best returns for investors as they cannot model relationships between hidden layer states efficiently, learn from them, and forecast into the future as evidenced by low prediction accuracies of 27% in a study by (Isenah and Olubusoye, 2014) for the Nigerian all share index. In addition different ARCH models results for the Nigerian stock exchange were also noted without any consensus on which is the best model.

Research on the value of computational finance intelligent systems to predict stock price movements in emerging and frontier markets is fewer in number although it is now growing. There is evidence that emerging and frontier stock markets are inefficient and this provides greater incentives to forecast returns (Lawal et al., 2017). However, a few concerns arise from the African stock market predictions initiatives. Firstly, most of the studies conducted make use of the Nigerian stock exchange dataset for statistical, fundamental, machine learning and deep learning models. Model generalizations cannot be done to other stock exchanges, hence instituting a need to conduct more prediction initiatives in other stock markets. Concerns have also been raised regards to the size of the datasets used being regarded as small like in the use of financial ratios for predicting the Nigerian stock exchange by (Ajekwe and Ibiamke, 2018). A need to make use of large datasets for developing prediction models is necessary.

Secondly, a lack of cross stock market analysis is noticeable in most studies giving rise of a need to do comparative studies for various stock market indices using the same prediction models. Where comparisons were done, there were for the same market. In addition, no adequate explanations were proffered for the difference in performance of the proposed algorithms. To date, there is no clear understanding of how African emerging and frontier markets behave and there are no explanations on the major drivers of stock price movements through computational financial intelligence.

Thirdly, past African stock market predictions are mainly classification problems focusing on up and down trends of stock prices. Few studies focused on the regression of time series using machine learning models. In addition, very few studies also focused on a combination of classification, regression and market direction predictions in one study, a gap that this study will implement as it contributes to the computational finance domain. In other words, this research is a combination of fundamental, technical and computational intelligent systems in predicting selected African stock markets.

Fourthly, few deep neural networks have been implemented in African stock exchanges. Where there have been implemented, consideration was on unidirectional architectures for a few stock exchanges. There are no bidirectional deep neural networks that have been applied to African stock exchanges. In addition, not much is known about the importance of deep neural networks to stock market predictions, either at African or international levels. Despite the fact that deep neural networks have been extensively used for other predictions, their application to financial time series is still scanty. A need to assess the usefulness of deep neural networks in frontier, emerging and developed financial markets is a necessity. Therefore, a study on the usefulness of deep neural networks to African stock markets is essential and should be benchmarked to developed stock exchange predictions. The majority of predictions done in African stock exchanges have not been benchmarked to developed stock markets.

Overall, African stock markets are small in size, illiquid, volatile, face issues on lack of trading transparency with the exception of the Johannesburg stock exchange and Egyptian stock exchange. The existence of persistent volatility swings in African stock markets demand prediction models with memory states to learn subsequent behaviour shaped by previous responses. Existing predictive models (including statistical and other machine learning models) are devoid of memory and sequential learning capability. Hence, a model which supports data driven decisions learning from its past and future states to aid investor decision making and improve on prediction accuracy is required. Furthermore, for different African stock markets, there is a need to understand the factors that influence the predicted stock market movement and why different stock markets react differently to various prediction models.

1.4 Research Objectives

The research study aims at addressing the following research objectives;

- To develop a model that can accurately and significantly predict the future stock price movements of African stock markets.
- To establish the factors that influence stock market movement in Sub-Saharan Africa.
- To investigate whether the factors that influence share prices differ amongst African markets.
- To investigate stock market inefficiency in African markets.

1.5 Contribution to the Body of Knowledge

Several share prediction models have been investigated in the literature to solve the financial time series forecasting problem and increase prediction accuracy (Araujo et al., 2015). Most stock market prediction initiatives in developing countries have been for Asian markets[2] and a few applications in African stock markets[3]have been noted, a gap that this research closed up by developing a stock price prediction model for African stock markets.

African stock markets are mostly frontier markets except for South Africa and Egypt which are emerging markets (MSCI World Index, 2018). Also, African stock markets are largely perceived as high risk investment zones faced with political, economic, regulatory and structural instability in addition to being thin and illiquid with the exception of South Africa and Egypt. Thus, the viability of African stock markets as investment zones depend on their potential to improve risk return trade-offs to global investors (Allen et al., 2011). African stock markets may offer global investors the opportunity to diversify their portfolios and increase return potential. The ability of this research to develop prediction models that can enhance investor decision making by reducing perceived risk and increasing return in African stock markets is a great contribution to African and global investment domains and in turn may attract more global investment to Africa.

In addition to the afore-mentioned, this study is important for a number of reasons. First, the study contributes to the limited literature on stock price prediction in Africa. The key discussion in this study answers to the return predictability possibility in African stock markets using ANNs and their variants even though African stock markets are considered very volatile, inefficient and illiquid. Development of stock price prediction models for African stock markets will add on to empirical evidence on the return predictability debates of African stock markets.

Second, this thesis is a major contribution to the knowledge of deep learning in stock price prediction initiatives. Most importantly, the deep learning models adopted in this study amount to a significant advancement in the prediction of stock markets and mostly in Africa. The deep learning models in this study have largely been used for speech-to-gesture generation, learning fashion compatibility, video description, image captioning, handwriting recognition, sequence-based problems,

[2]The application of ANNs for stock price prediction includes but not limited to the following stock markets; China Stock Exchange – (Chai et al., 2015; Cao et al., 2011); Bombay Stock Exchange – (Sundar and Satyanayarana, 2015); Frankfurter Stock Exchange- (Jarrett and Schilling, 2008) ; Nigerian Stock Exchange- (Akinwale et al., 2009; Isenah and Olubusoye, 2014;); DJIA and S&P 500 – (Anish and Majhi, 2016); NASDAQ – (Araujo, 2010; Wang and Zhu, 2010); Tehran Stock Exchange- (Zahedi and Rounaghi, 2015; Abbasi et al., 2014; Ghezelbash and Keynia, 2014;); Bucharest Stock Exchange –(Trifan, 2010); Petrobas –(Oliveira et al., 2013); Taiwan Stock Exchange – (Hsu, 2013); Karachi Stock Exchange – (Kiani, 2006); German Stock Exchange, Tokyo Stock Exchange and New York Stock Exchange – (Mandziuk and Jaruszewicz, 2011); Latin American Stock Markets –Argentina, Brazil, Chile, Mexico and USA- (Carvalhal and Ribeiro, 2007); Taiwan Stock Exchannge – (Lu, 2010); Nikkei 225 –(Lu, 2010; Lu et al., 2009) ; Saudi Stock Exchange- (Olatunji et al., 2013); Amman Stock Exchange- (Qasem et al., 2013); Istabul Stock Exchange – (Karymshakov and Abdykaparov, 2012); San Paulo Stock Exchange- (Luna and Ballini, 2012); Romanian BET Index –(Ruxanda and Badea, 2014); Johannesburg Stock Exchange – (Patel and Marwala, 2006); Indian Stock Market – (Mohapatra et al., 2012) and Asian Stock Markets – (Dai et al., 2012)

[3](Berradi and Lazaar, 2019; Mohamudally-Boolaky et al., 2019; Gyamerah et al., 2019; Ajekwe and Ibiamke, 2018; Okoro, 2017; Lawal et al., 2017; Olayiwola et al., 2016; Kareem and Adeoti, 2016; Isenah and Olubusoye, 2014; Adebiyi et al., 2014; Ajao and Wemambu, 2012; Agwuegbo et al., 2010; Akinwale et al., 2009; Patel and Marwala, 2006)

automatic speech recognition acoustic models[4] and their deployment to financial time series is a key contribution in prediction pursuits.

To the best knowledge of the researcher, this is the first study of undertaking a comprehensive comparison of DNNs in the field of stock market predictions. In addition, this is the first study to make an extensive comparison between unidirectional and bidirectional DNNs in stock market predictions with a cross market analysis perspective. Also, the application of deep neural networks in African stock markets has been scanty as evidenced through past African stock markets prediction initiatives[5] . This research extends the literature on stock price prediction using DNNs to the African context by looking at 10 Sub Saharan African stock markets[6] which were selected on the basis of market capitalization and this current study proffers explanations for why different stock exchanges react differently to the same prediction models.

Third, a growing body of literature outlines the better performance of ANNs in comparison to statistical models for time series prediction[7] . This study extends literature on the prediction capabilities of machine learning GAM nonlinear statistical approaches to stock market predictions. The better prediction capability of GAM compared to DNNs brings new theoretical insights into the field of stock price forecasting.

Fourth, new empirical evidence exhibiting that stock markets are not all the time efficient is generated in this study. This is exemplified by inconsistencies of the EMH and existence of calendar anomalies in African stock markets which can be exploited by investors for profitable gain. Therefore, this is in support of the AMH and CAS. Unlike most research studies that resorted to use of regression models with dummies to test for calendar anomalies, this current research introduces a machine learning technique, namely GAM for calendar anomaly detection. To the best knowledge of the researcher, this is the first research to use GAM for stock market calendar anomaly detection.

In addition, the fifth contribution is that through the use of a macroeconomic variable model, this research results bring substantial evidence to further support the arbitrage pricing. The study also extends empirical literature on key stock price drivers for African stock markets. The identified stock price drivers in African markets will help in the modification of asset pricing theory relevant for African markets by understanding the link between each macroeconomic variable and stock prices. New insights were found on the relationship between macroeconomic variables and closing price for the selected African countries. Amongst these insights include the fact that African stock markets under consideration react differently to macroeconomic variables in each country. However, unlike developed nations, African stock markets closing price indices in this study are negatively influenced by exchange rate.

In a nutshell, this thesis contributes empirically and methodically to computational finance literature especially in the price discovery, asset pricing and prediction

[4](Wang et al., 2016; Khandelwal et al., 2017; Chung et al., 2014)

[5](Berradi and Lazaar, 2019; Mohamudally-Boolaky et al., 2019; Gyamerah et al., 2019; Ajekwe and Ibiamke, 2018; Okoro, 2017; Lawal et al., 2017; Olayiwola et al., 2016; Kareem and Adeoti, 2016; Isenah and Olubusoye, 2014; Adebiyi et al., 2014; Ajao and Wemambu, 2012; Agwuegbo et al., 2010; Akinwale et al., 2009; Patel and Marwala, 2006)

[6]Botswana, Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tunisia, Zambia and. Zimbabwe

[7](Reid et al., 2014; Araujo, 2010; Kumar and Thenmozhi, 2009; Senol and Ozturan, 2008; Abdelmouez et al., 2007; Avci, 2007; Altay and Satman, 2005; Egeli et al., 2003; Desai and Bharati, 1998; Hill et al., 1994)

debates. New methodologies inclusive of deep neural networks and generalized additive models to asset pricing in an African stock markets are the key contributions of this research.

1.6 Benefits of Study

The everyday stock market trader or investor as well as financial analysts will greatly benefit from the discovery of an optimal prediction model for stock price prediction. The investors' trading decision making process will be enhanced with the use of such prediction models and be in a position to achieve maximum financial gain from trading at less risk. As part of knowledge discovery in databases, this study made use of intelligent data analysis tools to extract potentially useful information from data in order to make knowledge driven decisions. Hence stock market trading and investing are done from a scientifically informed position contributing immensely to investment risk management and return maximization. Investors can form an understanding of the price formation process which is fundamental to achieving higher returns and lowering risks. In addition, the use of algorithmic finance tools for price discovery, asset pricing and prediction therefore results in improved price discovery for fast traders and high frequency traders.

The research findings have vast implications for policy makers. From a policy perspective, policymakers can use stock price predictions, a leading economic indicator (Mitchell and Burns, 1938) to identify turning points in an economy, hence determine if a recession is likely to occur and take appropriate actions. An understanding of the relationship between stock prices and macroeconomic variables is critical. If policy makers understand such relationships, they can formulate either expansionary or contractionary policies to stabilize markets. Therefore, this study is a useful guide to traders, investors, and asset managers in making trading and investment decisions and for policy formulation by financial market regulators as they maintain and monitor the order of African stock markets.

1.7 Structure of the Thesis

This thesis is divided into different chapters as follows;

- Chapter 1: Introduction to the thesis topic
- Chapter 2: Theoretical Underpinnings of the Study
- Chapter 3: Literature Review
- Chapter 4: Stock Price Prediction Models
- Chapter 5: Research Methodology
- Chapter 6: Research Findings and Discussions
- Chapter 7: Summary and Conclusions

1.8 Chapter Summary

This chapter was an introduction highlighting the importance of the study and the knowledge gaps it intended to address with the use of different prediction models in stock price forecasting. Following up on this chapter is a systematic review of theories underpinning stock price prediction.

Chapter 2

Theoretical Underpinning of the Study

2.1 Introduction

This chapter presents various theoretical underpinnings that guide this study on stock price prediction. The chapter is organised as follows: section 2.2 surveys literature on the Efficient Market Hypothesis (EMH) whilst section 2.3 discusses the Adaptive Market Hypothesis (AMH). Section 2.4 looks at the Complex Adaptive System (CAS) Theory and section 2.5 focuses on the Arbitrage Pricing Theory (APT). A chapter summary concludes the chapter.

2.2 Efficient Market Hypothesis

Efficient markets are markets with enormous numbers of rational, profit maximizers actively competing with each other trying to predict future market values of individual securities, and where current important information is almost freely available to all participants. Alternatively, the expression "market efficiency" refers to the informational efficiency of financial markets.

Efficient markets are explained through the EMH which asserts that asset prices fully and instantaneously reflect all available and relevant information (Fama, 1970). In that regard, stock prices reflect all the available information about the value of a firm, and therefore there is no possibility of economic profits (Plastun et al., 2020). In other words, the reaction of the market is spontaneous for information, no one can utilize the public information to acquire higher returns other than the return that is adjusted via market risk and no one can beat the market (Zhang et al., 2017b). None of the market participants can systematically get a return above the market (Al-Khazali and Mirzaei, 2017). It is argued that financial asset returns should follow a memory-less stochastic process since the EMH assumes that past price movements have no predictive power of future prices and returns of financial assets (Chu et al., 2019).

The EMH is explained through the weak, semi-strong and strong forms of efficiency. Under the weak form efficiency, there are no possibilities of identification of any deterministic patterns in time series behaviour. Thus, the EMH from an arbitrage perspective entails no obtaining of systematic abnormal profits by using past information (Ferreira and Dionisio, 2016). This means even uninformed investors buying a diversified portfolio at the tableau of prices given by the market will obtain a rate of return as generous as that achieved by the experts (Malkiel, 2003). In other words, it means that according to EMH, traders cannot predict and beat the market in order to make abnormal profits (Plastun et al., 2019a). The only way a trader or investor can attain an outsized profit is by investing in higher risk assets (Titan, 2015).

Concurring with the above view is (Charles et al., 2017) who postulates that under the weak form efficiency, the information set is made up of past prices and returns. Future prices and their returns are purely unpredictable based on past information, and thus arbitrage opportunities are competed away. The authors state that asset prices follow a martingale process and its increments (returns) are characterized by a martingale difference sequence (MDS), where the returns are independent and uncorrelated with past events. In other words, when the market is considered to be in the weak form, the asset returns are simply unpredictable from previous data (Ghazani and Araghi, 2014).

The weak-form efficiency usually involves testing of two hypotheses; the random walk hypothesis (RWH) and the martingale difference hypothesis (MDH). The RWH is directly consistent with the EMH in that it assumes that asset prices resemble a random walk process, thus prices change randomly and cannot be predicted. The MDH undertakes that the best predictor of a time series given an information set is simply its unconditional mean. The applicatory part of the EMH to asset pricing has one implication which is that no amount of information would be useful in helping one to make predictions about an asset's returns (Chu et al., 2019). Achievable returns by an investor are dependent on the degree of risk undertaken.

The other EMH forms are the semi strong and strong form efficiencies. Information, precisely public information, is efficiently echoed in stock prices under the semi-strong form (Al-Shboul and Alsharari, 2019). The semi-strong assumes that financial assets' prices mirror, at any moment, all the information existent in the market, including historical prices information (Titan, 2015). Prices under the semi-strong form change rapidly and without biases to incorporate any new or any other new public information. In cases where the so- called semi strong of the EMH is present on capital markets, use of technical or fundamental analysis cannot determine the way an investor should split his funds so as to obtain profitability higher than that achieved by investors.

The strong form efficiency assumes that asset prices incorporate all the available information which include historical financial information (weak form), all new public information (semi-strong) and private information regarding a financial asset. All the relevant information, such as private information, which is accessed monopolistically by an individual or group of investors, is reflected by the stock prices. Therefore, there is no scope for making abnormal profits since investors are equally informed (Al-Shboul and Alsharari, 2019).

Overall, EMH proponents argue that financial markets are perfectly capable of aggregating information of all investors, which in turn leads to efficient markets and that financial markets cannot be predicted (Titan, 2015). The key notion of the EMH is that prediction of future prices is not possible and cannot be forecast due to the random walk behaviour of prices. EMH assumes that financial markets react immediately to new information making it impossible to beat the market using that information. In other words, the EMH does not allow for any variation in the degree of efficiency over time or for the efficiency of the market to be influenced by other market factors (Chu et al., 2019).

In reaction to the afore-mentioned assertion of no variability in market efficiency, the validity of the EMH has being increasingly contested and this has become a long standing debate in the field of finance. Inconsistencies with the EMH have been noted owing to the growing evidence of the existence of financial anomalies in the financial markets around the world which point to the fact that return predictability in financial markets is possible (Wasiuzzaman, 2018).

It is on this premise that this current research tests the tenets of EMH by investigating whether the share price can be predicted, especially in African stock markets. The key issue is to assess if African stock markets are efficient or not through return predictability; to assess if the EMH evolves to other factors other than information which can influence the stock market performance, and thus contribute to the ongoing scholarly and professional debates on the EMH.

2.3 The Adaptive Market Hypothesis (AMH)

There is a long standing debate between EMH and behavioural finance on whether financial markets are informationally efficient. Against the background of this debate, (Lo, 2005) contended that the informational efficiency of a market is time varying and driven by the fundamental rules of economic selection, known as the Adaptive Markets Hypothesis (AMH). Resultantly, it is increasingly accepted that the informational efficiency of a market is fluctuating over time (Yang et al., 2019).

The AMH is an adjusted framework to the EMH and is centered on the concept of bounded rationality and the evolutionary principle (Kim et al., 2011). A bounded rational investor is said to display satiating rather than optimal behavior. The belief is that optimization can be costly and market participants with restricted access to information or capabilities to process the information are purely engaged in achieving a satisfying outcome. (Lo, 2004) argues that this satisfying outcome is attained through a trial and error and natural selection. Thus market participants adjust to the continually varying environment and rely on heuristics to make investment choices. A need for prediction tools that do not rely on heuristics is paramount, a gap that this current research aims at achieving.

It is also believed that the efficiency of the market is conditional upon changing market conditions (Ghazani and Araghi, 2014). Increasing evidence of the application of the AMH is noticeable with many studies on the subject (Zhou and Lee, 2013; Urquhart and Hudson, 2013; Lim et al., 2013; Kim et al., 2011; Lo, 2004, 2005). The six key concepts of the AMH are that individuals take action based on their own self-interest; they make mistakes; learn and adapt; competition drives adaptation and innovation; natural selection shapes the market and evolution determines market dynamics (Lo, 2004) .

Viewed as an evolutionary alternative to market efficiency, the AMH under which the EMH and calendar anomalies can co-exist in an intellectually consistent manner has several implications .The key implications of the AMH are that the risk premium fluctuates over time according to the stock market environment and demographics of investors. Second, arbitrage opportunities do occur from time to time as do profit opportunities connected to market timing. However, as they are exploited they vanish, and new opportunities are persistently being created. Rather than a direct movement to a higher degree of efficiency, the AMH implies that complex market dynamics such as trends, panics, bubbles and crashes are continually witnessed in the market ecology (Urquhart and McGroarty, 2014). Therefore the implication is that return predictability can arise from time to time due to altering market conditions (e.g. cycles, bubbles, crises etc.) and institutional factors (Kim et al., 2011; Charles et al., 2017; Ghazani and Araghi, 2014).

Third, the performance of investment strategies either as successful or not varies over time depending on the particular market environment. Strategies considered to exploiting arbitrage opportunities may weaken for a while, and then return to profitability when environmental conditions become more favorable (Charles et al., 2017). A result of this matter is that market efficiency is not an all or nothing condition and changes over time as calendar anomalies induce new profit opportunities continually (Kumar, 2016). Thus convergence to market efficiency is neither guaranteed nor likely to occur since new profit making opportunities are continually created. Fourth, as a result of the ever changing market condition, innovation is the key to survival (Yang et al., 2019; Urquhart and McGroarty, 2014).

In agreement to this changing market efficiency viewpoint are (Al-Shboul and Alsharari, 2019) who argue that as the degree of information flow varies over time, one can anticipate that stock prices may behave differently over time, causing modifications in the level of market efficiency from one form efficiency to another. In addition, adaptation to these changing market conditions can make one can achieve a consistent level of expected returns (Chu et al., 2019).

In consideration of African stock markets, (Alagidede, 2011) provides evidence of return predictability in six African indices[1] . The presence of long term memory in the selected African stock market prices provided further evidence that contradicts the weak form market efficiency. With this in mind, it is therefore possible to predict returns over the range of dependence. Individual time varying returns are predictable and empirical stylized facts such as leverage effect and leptokurtosis were found to be prevalent in the selected African stock market returns. These results are consistent with the AMH. Further evidence of stock market return predictability for African stock markets was shown in a study by (Dyakova and Smith, 2013) by examining the Bulgarian stock exchange. Stock price indices (SOFIX and BG40) were found to deviate from the martingale in some periods and were consistent with the AMH. This current study looks at eleven stock markets, ten African stock markets and one United States stock market to find further evidence of the return predictability through use of machine learning techniques.

The AMH was able to explain varying stock market returns in the following markets; US, UK, Japan, Canada, France, Switzerland, Germany and Italy (Plastun et al., 2019b); US and China (Yang et al., 2019); Islamic Stock Indices (Al-Khazali and Mirzaei, 2017); S&P 500, FTSE100, NIKKEI225 and EURO STOXX50 (Urquhart and McGroarty, 2016);Tehran Stock Exchange (Ghazani and Araghi, 2014; US stock market (Urquhart and McGroarty, 2014) and Dow Jones Industrial Average in US (Kim et al., 2011).

The AMH is receiving growing attention in academic literature as researches study the implications of the AMH in stock markets (Plastun et al., 2020; Yang et al., 2019; Al-Khazali and Mirzaei, 2017; Kumar, 2016; Urquhart and McGroarty, 2014; Dyakova and Smith, 2013; Ghazani and Araghi, 2014; Kim et al., 2011) The existence of calendar anomalies in stock markets attests to the fact that markets are not efficient all the time. Evidence of AMH through calendar anomalies acts a proxy for market inefficiency.

2.3.1 Calendar Anomalies

Investors search for opportunities to increase returns continually and make use of varying trade strategies. Amongst these strategies is the use of calendar anomalies in the stock markets to attain abnormal profits. Investors and traders generate their trading strategies based on the identified calendar anomalies (Norvaisiene et al.,

[1] Kenya, Egypt, Tunisia, Morocco, South Africa and Nigeria

2015). Calendar effects are amongst the prominent reasons for the occurrences of abnormal returns (Zhang et al., 2017b). Calendar effects include time of the day effects, day of the week effects, week of the month effects, month of the year effects, turn of the month effects, Halloween effect and Mark Twain effect.

Day of the week effect results in a different return for each day of the week with the lowest and negative returns cited to occur on Mondays and highest returns attained on a Friday. Studies on the day of the week just like any other effect are continually producing varied results. (Diaconasu et al., 2012) examined the presence of the day of the week and the month of the year effects in the Romanian equity market using Bucharest stock exchange returns. They found the presence of a Thursday effect and did not find any Monday or January effect since Monday returns are positive though not statistically significant and coefficients of the month of the year are negative though not statistically significant. The two indices, BET and BET-C both document a Thursday effect and a lower return on Fridays in the case of BET-C. Analysis of the entire period provides evidence of higher returns in April and July and the absence of January effect in both indices. Experiments were done through a regression with dummies model.

The January effect is evidenced by higher stock returns in January as compared to the other months of the year. Using a regression with dummies model, (Norvaisiene et al., 2015) investigated seasonality in the Baltic stock exchanges (Nasdaq OMX Tallinn, Nasdaq OMX Riga and Nasdaq OMX Vilnius). Evidence from these studies revealed presence of the Halloween effect in Estonia and Month effect in Estonia and Lithuania. Daily return in January averaged 0.25% and 0.17% for Estonia and Lithuania respectively. Investors in Estonia may use the Halloween effect and earn a higher return during the 'winter' period as compared with the return on investment during the 'summer' period. (Alagidede, 2013) found the presence of the January effect for Egypt, Nigeria and South Africa, a February effect for Morocco, Kenya, Nigeria and South Africa. However, no monthly seasonalities were found for Tunisia.

(Plastun et al., 2019a) examine the evolution of the Halloween effect in the developed stock markets of the US, UK, French, Canadian, German and Japanese. The Halloween effect indicates that returns between November and April are higher than in the other months of the year. The key findings of (Plastun et al., 2019a) were that the Halloween effect only became detectable in the middle of the 20th century and is still present in these developed markets. This provides investors an opportunity to develop trading strategy to beat the market. It is also noted that the Halloween effect in the US and the other developed markets is consistent with the AMH.

In another study by (Plastun et al., 2019b), they investigated calendar anomaly evolution of the US stock market using the Dow Jones Industrial Average to test for the week effect, turn of the month effect, turn of the year effect and the holiday effect. Results from this study show that the 'golden age' of calendar anomalies was in the middle of the 20th century. However, since the 1980s all calendar anomalies vanished, which is consistent with the EMH. Therefore, the study results provide resounding evidence that the US market evolved from being inefficient with a number of calendar anomalies to being efficient such that it is difficult to find 'holes' in price dynamics that can produce exploitable profits.

Contrastingly, (Zhang et al., 2017b)found out that in the US markets, the Monday effects are most prominent. (Urquhart and McGroarty, 2014) also find evidence of the Monday effect, January effect, turn of the month effect and Halloween effect in the USA markets. Whilst evidence from (Plastun et al., 2019a) is consistent with the EMH, studies by (Zhang et al., 2017b) and (Urquhart and McGroarty, 2014) are consistent with the AMH.

Additionally (Zhang et al., 2017b) also found out the presence of Monday Effects in the Chinese Markets and in Argentina, Poland, Italy and Singapore. Wednesday effects were found in stock markets in Mexico, Indonesia, Germany, Switzerland, Australia, Japan and New Zealand. They also found out Thursday anomalies in stock markets in Czech Republic and Philippines whilst Friday anomalies were identified for stock markets in Brazil, Chile, Russia, Turkey, India, Malaysia, Spain and Hong Kong. Investors can use such information to predict the stock markets by utilizing calendar anomalies to maximize their returns on investment. This attests to the fact that different days of the week are increasingly being noticed for different stock markets as the respective markets continue to adapt and change.

(Agrawal and Tandon, 1994) conducted a study of five calendar anomalies (weekend effect, Friday-the-thirteenth effect, the turn-of-the-month effect, the end-of-December effect and the January effect) for 19 countries[2] . Monday returns were found to be the lowest and negative for nine out of the 18 countries, which was consistent with findings in the USA. In eight of the other countries, lowest returns were found on a Tuesday. Friday return is significantly positive in all the countries, except Luxembourg. The Friday the-thirteenth effect was not found in all countries. The January effect was established in 14 country indices and a significant monthly seasonality in many countries was also noted. Large returns were also found during pre-December holidays in eleven countries and during the inter-holiday period in fourteen countries. Unlike the USA, pre-Christmas returns were positive and significant in seven countries. In contrast, only South Africa, an emerging market was found to have pre-holiday effects (Alagidede, 2013).

(Chen and Daves, 2018) focus their study on investigating the January sentiment effect in the US market. Notably, the authors argue that individual investors' economic outlook in the month of January may impact their asset allocation decisions and demand for risky assets for the remainder of the year. The empirical results of this study are consistent with the aforementioned in that results reveal that the degree and direction of the January index of consumer sentiment changes are positively related to subsequent monthly returns from February to December.

Another study by (Cao et al., 2019) investigated the existence of five investment related anomalies in the Australian stock market. It was found out that cross sectional stock returns were negatively related to asset growth, net operating assets, inventory growth and investment- to- assets whilst positively related to asset tangibility. The authors identified that the use of the q-theory to explain these anomalies was not persuasive.

Similarly, (Nayaran and Zheng, 2010) conducted a study to find out the role of market liquidity risk in determining cross sectional stock market returns. The objective of the study was to find out if financial anomalies with or without the inclusion of market liquidity risk in the Chinese stock market can explain cross-sectional stock market returns. Size, the book-to-market ratio and turnover rate were responsible to explaining cross-sectional stock market returns when the market liquidity risk is imposed on the Chinese market. Hence, investors can make use of such anomalies for stock return prediction.

In another novel study, (Cao and Wei, 2005) looked at stock market returns and the temperature anomaly. Working with eight international stock indices[3] , it was

[2]Australia, Belgium, Brazil, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Singapore, Sweden, Switzerland, UK and USA.

[3]US, Canada, Britain, Germany, Sweden, Australia, Japan and Taiwan.

established that feelings and emotions affected people's decision making and mood is affected by the environmental factors such as weather conditions. Low temperatures were noted to cause aggression whilst high temperatures can cause apathy and aggression. An overall negative correlation between temperature and stock returns was noted in the eight countries under consideration.

Consideration of calendar anomalies for an emerging market were conducted for the Athens Stock Exchange in Greece using a stochastic dominance analysis.(Al-Khazali et al., 2008). A strong day effect with the highest observed returns was noted on Friday whilst the lowest returns were on Tuesday. The findings of the Tuesday anomaly are consistent with studies on non-Greek markets such as Singapore, France, Australia and Japan. The week effect is not so significant in the Athens stock exchange, even though the first week of the month yielded slightly higher returns than other weeks of the month. In addition, the January effect was found though it was not statistically significant.

(Seif et al., 2017) tested for the month of the year, other January, day of the week, holiday and week 44 stock market anomalies in nine advanced emerging markets[4]. No evidence of the January effect was found whilst evidence for month of the year, the day of the week effect, the holiday effect and week of the year effect was noted. A Friday type effect that occurs on the last trading day of the week, which is termed the Wednesday effect in this study owing to the fact that Wednesday, is the last day before the weekend in the leading markets in Gulf Cooperation Council[5] is noticeable. Friday returns were noted to be higher in all GCC markets. The evidence shows the presence of an end of week (Friday effect) anomaly in all GCC markets. A statically significant positive December effect is noted for five GCC market indices (Kuwait, Muscat, Qatar, Saudi Arabia and Dubai). Thus, instead of the positive January effect documented in western countries, markets in the GCC exhibit a December effect. Such empirical evidence is at odds with the EMH.

Interestingly, (Caporale and Zakirova, 2017) argued in favour of the EMH. Their study on the Russian stock market to investigate calendar anomalies (January effect, day of the week effect and turn of the month effects) revealed that when transaction costs are considered in the analysis, calendar anomalies disappear. Though the calendar anomalies are identified, they cannot result in gaining abnormal profits nor in beating the market as a result of transaction costs which are proxied by the bid-ask spread in this study. Evidence for calendar anomalies and profitable strategies based on them disappear, suggesting that markets (Russian stock market, in this case) might in fact be informationally efficient.

A novel study by (Wasiuzzaman, 2018) considered the effect of religious anomalies (the Hajj pilgrimage) on the Islamic stock markets. Results reveal existence of a statistically insignificant negative influence of the Hajj on stock returns. This implied that the daily returns on Islamic stock markets are negative during the Hajj period. In addition, they also found out that there is increase in volatility during the Hajj pilgrimage period owing to less participation in the stock market by the religiously observant investors. Such results add on to the empirical literature on the significance of culture or religion in influencing investor behaviour, hence adding on to studies on stock predictability and investor irrationality. Looking at the Baltic stock exchanges, (Norvaisiene et al., 2015) found evidence of stock market calendar anomalies. The month effect was predominant in Estonia and Lithuania exhibiting

[4]Brazil, the Czech republic, Hungary, Malaysia, Mexico, Poland, South Africa, Taiwan and Turkey (based on FTSE's country classification)

[5]Abu Dhabi securities market, Bahrain stock exchange, Doha securities markets, Dubai financial market, Kuwait stock exchange, Muscat securities market and Saudi capital market.

higher returns in January compared to other calendar months. The Halloween effect was also noted for Estonia. Perfect timing of such anomalies can result in abnormal profits.

It can be noted that due to time varying market conditions and differing stock market characteristics, changing calendar anomalies were noted. There are different hypotheses to explain the existence of these calendar anomalies. The day of the week effect in which Monday returns are very low and Friday returns very high can be explained through various hypotheses. Most investors usually trade less on Mondays as compared to other week days which makes the returns lower (Plastun et al., 2019b). In addition, mood also plays a key role in that investors who start the week on a low mood, will eventually trade less, hence dampening stock prices and returns. Different time zones also contribute to low Monday returns for other countries especially those affected by big stock market players (Seif et al., 2017).

The January effect is mostly explained in terms of the tax-loss selling hypothesis. Most investors prefer to sell their securities prior to year end in order to claim capital loss for tax purposes. In January, they reinvest their money causing security prices to rise. With such actions, security prices fall in December and rise in January with significant returns realizable in the month of January (Kumar, 2016).

Turn of the month effect is when investors make purchases during the start of the calendar months and delay sales to the middle of the month in order to capture the higher than usual returns that accrue in the early days of the calendar months. No explanations have been put forth for the Halloween effect, in which the month of May signals the start of a bear market where investors would rather sell off and hold cash. They wait till November when the market is bullish. Returns between November and April are the highest when compared to the other calendar months. Other hypotheses for calendar anomaly detection include the inventory adjustment hypothesis (public holiday effect), seasonal affective disorder (week 44 effect), tax-loss selling and window dressing for the month of the year effect (Seif et al., 2017).

Given the dearth of empirical studies on calendar anomalies in emerging and frontier markets, results found for such markets would assist in the better understanding of stock returns across such markets. In addition, key to the above findings is that investors can make use of the results in developing asset pricing models that are powerful predictors in emerging and frontier markets, hence improving their investment decision making. This current research study is premised on the examination of the AMH through evidence of calendar anomalies and return predictability for African stock markets. Unlike most studies that have made use of regression models with dummy models, this study adopts the use of machine learning techniques to establish calendar effects and contribute to the long standing debate of validity or non-validity of the EMH. Financial intelligent computing decision making can enable African stock market investors to maximize on their returns.

2.4 Complex Adaptive Systems Theory

Investors are believed to be irrational, operating with incomplete information and relying on varying decision rules. This is called the complex adaptive system as in (Mauboussin and Boston, 2002). In a complex adaptive system, the sum is greater than the parts. Therefore, understanding of the stock market cannot be done by focusing on individual analysts but an aggregation of many players' decisions.

Self-organised criticality is a direct function of the dynamic interactions among the agents in the system. A central characteristic of the complex adaptive systems is 'critical points'. This means that large changes happen as a result of the accumulation of small stimuli. In other words, CAS is best explained by aggregation, where large scale behaviours are collective interactions of many less-complex agents. In capital markets, the behaviour of the market emerges from the interactions of investors (Mauboussin and Boston, 2002; Brock, 1991). The stock market is viewed as a stock network comprised of small world network characteristics (Nie et al., 2015). According to (Holland, 1992), CAS exhibit evolution, aggregate behaviour and anticipation. A key feature distinguishing CAS from other complex systems is that CAS form and use internal models to anticipate the future, basing current actions on expected outcomes.

Also key for CAS is adaptive decision rules. Agents within a CAS take information from the environment and combine it with their own interaction with the environment to derive decision rules. In turn, various decision rules compete with one another based on their 'fitness', with the most effect rules surviving and this process requires adaption. The concept of adaptive decision rules is consistent with the disappearance of anomalies in that as investors seek more profit opportunities, they refine their decision rules to compete anomalies away from the system. Thus, complex systems have an ability to learn from their experience (Shaduri, 2008). Such characteristics are in tandem to the AMH's adaptability role in changing environments.

(Manson, 2001) breaks complexity research intro three broad arms namely, algorithmic complexity, deterministic complexity and aggregate complexity. Algorithmic complexity contends that the complexity of a system lies in the difficulty faced in describing system characteristics whilst deterministic complexity postulates that the interaction of two or three key variables can create largely stable systems prone to sudden discontinuities. Concerned with how individual elements work in concert to create systems with complex behaviour is termed aggregate complexity. In addition, in aggregate complexity, the complex system is defined more by relationships than by its constituent parts and is adopted as one of the foundations for this current research.

2.5 The Arbitrage Pricing Theory (APT)

There is an ongoing debate in the field of finance on what really moves stock prices and in turn stock returns. Amongst many variables that explain movement of stock prices, macroeconomic variables have been widely accepted as major drivers thereto (Azeez and Yonezawa, 2006). Consensus amongst researchers is that expected returns are sensitive to more than a single factor; hence the introduction of multi factor models such as the APT of (Ross, 1976). As an alternative to the CAPM, the APT forms an important branch of asset pricing theory (Connor and Korajczyk, 1995). Stock returns are influenced by a variety of systematic economic news in the form of economic state variables (e.g. industrial production, inflation, term structure, consumption, oil prices etc) and unanticipated events. Stock returns are priced in accordance to their exposures to such systematic influences (Chen, 1983).

The APT is premised on an underlying assumption that asset returns follow a linear k-factor model (Lehmann and Modest, 1988). In other words, each asset return is linearly correlated to a number of k common 'global' factors plus its own idiosyncratic disturbance (Chen, 1983). One key advantage of using specified economic variables as APT factors is that it provides a link between various corporate strategies and the ever-changing economic environments (Chen and Jordan, 1993).

Though there is no formal theoretical guidance in selecting the pre-specified macroeconomic variables and number of factors to be considered, the following five variables are commonly regarded: the unexpected change in term structure; the unexpected change in risk premiums; the change in expected inflation; the unexpected inflation rate and the unexpected change in the growth rate in industrial production (Chen and Jordan, 1993; Ferson and Korajczyk, 1995; Elder, 1997; Azeez and Yonezawa, 2006).

The choice of these variables is premised on the fact that stock returns are influenced by macroeconomic variables and any changes in any of these variables may be expected to change the investor's and trader's perceptions of future cash flows and thus affect current prices (Azeez and Yonezawa, 2006). Given the underlying premise of this theory, the proper identification of the k factors responsible for driving stock prices and implementation of the correct prediction model will result in financial wealth maximization. Though the APT has been extensively applied to most developed markets, the emphasis of this research is to determine if the same k factors responsible for driving stock prices in developed markets can be used to predict stock prices in emerging and frontier markets. In this research, a macroeconomic variable model was used to explain the set of macroeconomic variables that influence share price movements in African stock markets.

2.6 Chapter Summary

This chapter looked at the Efficient Market Hypothesis (EMH), Adaptive Markets Hypothesis (AMH), Complex Adaptive Systems Theory (CAS) and the Arbitrage Pricing Theory (APT) to explain how stock markets adapt to changing macro-economic environments. In addition, the chapter summarized the potential for stock return predictability and how the aforementioned theories assist in explaining stock price movements in African stock markets. The next chapter is a review of literature on stock price predictability.

Chapter 3

Literature Review

3.1 Introduction

This chapter presents various theoretical and empirical literature on stock price prediction. The chapter is organized as follows: section 3.2 discusses the role of stock markets in investors' wealth maximization. Section 3.3 that follows looks at the characteristics of stock markets whilst section 3.4 focuses on factors that influence the stock market performance both on a macro and micro level. Section 3.5 reviews literature on various stock market prediction techniques. The conceptual frameworks for this research are tabled in section 3.6 and a chapter summary concludes the chapter.

3.2 Role of Stock Market

3.2.1 Role of Stock Market in National Economic Growth

The stock market has performed three important roles towards national economic growth and development. First, stock markets are known to provide liquidity to owners of various financial assets and this is considered as the main role of stock markets (Almomen, 2016; Masoud, 2013; Ezeoha et al., 2009). The liquidity produced by the stock markets makes investments less risky as it permits investors to buy or sell equity without locking in their savings for a long time horizon. In addition, a highly liquid stock market is an incentive for more investments as a result of the reduction in uncertainty associated with investing in the stock market (Pan and Mishra, 2018).

Second, stock markets are very crucial in the capital formation process for economic growth. Well-functioning stock markets enable efficient allocation of resources (Fufa and Kim, 2018). The stock market acts as a platform to raising and allocation of long term capital and award investor's opportunities to invest their surplus funds (Dagar, 2014). Therefore, the key impact of stock markets on the economy is that it assists in savings mobilization through the provision of attractive investment and savings vehicles. An increase in the savings rate facilitates higher capital formation and economic growth (Sulong et al., 2018; Ngare and Nyamongo, 2014; Enisan and Olufisayo, 2009). In this regard, the stock market through its capital formation and allocation function will act a barometer of economic performance (Dagar, 2014). The strength of the stock market in resource mobilization is reflective of the strength of the country's economy (Almomen, 2016).

Stock markets also play an essential role of risk reduction by offering opportunities for risk diversification (Ezeoha et al., 2009). To this end, stock markets offer domestic and international investors varying vehicles for trading, pooling and diversification of risk (Enisan and Olufisayo, 2009). Investment risks are also reduced owing to the ease at which equities are traded (Ngare and Nyamongo, 2014). In addition, the stock market also helps in the reduction of the cost of transacting. In providing financial information and projects relating to various financial assets available in the stock market with regard to the information of the financial situation of companies, a reduction in the cost of access to such information in terms of effort, time and risk is noted (Masoud, 2013).

3.2.2 Role of Stock Market in Investor Wealth Maximization

Despite the enormous challenges of stock price prediction, investors, researchers and practitioners are continuously looking at ways of perfecting stock price prediction that can yield significant profit arising from market inefficiencies. The payoffs from successful prediction motivate researchers, investment professionals and average investors to continuously pursue such accomplishments (Oztekin et al., 2016; Wang et al., 2016; Reid et al., 2014; Hsu, 2013; Liang et al., 2011; Lawrence, 1997). Successful forecasting of stock prices is believed to turn out into substantial monetary rewards (Wei, 2016; Gocken et al., 2016; Nayak et al., 2015) . (Liang et al., 2011) postulate that in any dynamic market place, system (s) that can consistently select winners and losers would make the owner of the system(s) very wealthy. Thus, predicting stock performance is a very large and profitable area to pursue (Kim and Han, 2016).

The ultimate key in attaining superior risk adjusted profits from investment is the ability to find out the suitable trading time with the minimum risk of trading (Dash and Dash, 2016). Correct prediction of future market trends is a prerequisite to be a successful financial trader in financial markets (Bagheri et al., 2014). Stock price prediction initiatives improve trading strategies or investment decisions for market players (Zhong and Enke, 2017; Anish and Majhi, 2016).

The advent of data mining in financial time series predictions has provided pathways for investors to take proactive and knowledge-driven decisions in order to achieve successful gain with less investment risk (Dash and Dash, 2016). In the past, most researches focused on stock price prediction only with a few looking at trading decisions. In order to make profit from stock investments, the investors need to establish the correct time to trade in addition to the stock price, hence innovations in machine learning and other computational intelligence practices enable the investor or trader to make an informed decision that reduces investment risk and increase profitability (Chang et al., 2016). Thus, data mining and machine learning approaches have made it possible for investors, traders and related stakeholders to solve the financial stock trading decision problems.

Since future stock prices are determined scientifically, the key research issues in prediction are the accuracy of reliability prediction (Shan et al., 2015). An increase in prediction accuracy entails increased profitability. Any prediction result close to or equal to 100% is the most desirable. Quantitative investment models are able to provide accurate stock market prediction and help investors to avoid risks of mispricing and irrational trading as a result of psychological factors (Zhang et al., 2014) . Therefore, it can be noted that the analysis of financial time series is very important in guiding investment and trading decisions (Laboissiere et al., 2015).Accurate stock price prediction also aids in policy making since stock prices are considered as one of the most important indicators of a country's economic growth. The major reason for the increased need for stock market predictions is that it affords an avenue for government administrators to maintain and monitor the order of stock markets (Duan et al., 2013).

3.3 Stock Markets Characteristics and their Prediction Challenges

Stock markets are viewed as model complex systems composed of many agents interacting amongst themselves in a highly nonlinear way (Bonanno et al., 2001). A complex system is an organization of individual agents, who have the liberty to act in various ways that are not all the time predictable, and whose actions are unified such that one agent's actions alter the environment for other agents (Grobman, 2005). Complex systems are a composite of many interacting units called agents so that the combined behaviour of these parts is more than the sum of their individual behaviours (Newman, 2011; Mitchell and Newman, 2001).

Stock markets can be viewed as complex, evolutionary and nonlinear dynamical systems; hence stock forecasting is characterized by data intensity, noise, non-stationary, high uncertainty and hidden relationships (Shan et al., 2015; Liu and Hu, 2013). Concurring with this notion are (Sanjeev, 2015) and (Lu, 2013) who view financial markets as nonlinear dynamical systems, complex, evolutionary, highly noisy, irregular, random, seasonal and chaotic in nature.

There are complex and time varying dependencies between factors affecting stock price (Mandziuk and Jaruszewicz, 2011). Complex behaviours within financial time series like noise, trends, volatility and irregularities make its prediction a challenge (Araujo, 2012) and the chaotic nature of financial time series a popular and challenging subject amongst researchers, academics and practitioners (Muhammad and Saeed, 2011). Therefore, owing to the complexity of stock markets, predicting them is thus a severe challenging task for investors, academia and practitioners (Zhong and Enke, 2017). Stock prediction is therefore regarded as difficult owing to the uncertainties involved (Zhang et al., 2016; Kumar et al., 2016; Patel et al., 2015a).

Regardless of the fact that in stock market prediction debates, stock market prediction is considered as one of the most challenging tasks of financial time series making forecasting a challenge (Shan et al., 2015; Adebiyi et al., 2014; Lu, 2013; Wong and Versace, 2012; Araujo, 2012), it is still regarded as one of the most rewarding initiatives if accurate predictions are done.

It was the thrust of this current research to contribute to increasing prediction accuracy with a focus on African stock markets. Whereas developed markets are known to be efficient and highly liquid, developing stock markets exhibit illiquidity and inefficiency. A need to come up with a prediction model to capture these unique African stock market characteristics becomes a necessity for the benefit of traders, investors and researchers. New innovations in the ANN domain include the use of deep neural networks. It was also the intent of this research to develop and apply these models to stock price prediction and ascertain if they are improving on prediction accuracy.

3.4 Factors that Influence the Stock Market Performance

3.4.1 Macroeconomic Factors in Share Price Movements

There are various macroeconomic factors that are found to influence the share price and the debate on stock price determinants has not been conclusive. Four mostly used economic variables to explain stock market fluctuations include exchange rates, money supply, interest rates and inflation (Barakat et al., 2016). Forceful changes in stock prices can result in negative implications for an economy. This explains the increased number of finance studies on macroeconomic variables and stock prices or returns in the past few decades and thus drawing the attention of researchers, policy makers and financial investors.

Stock markets can be used as economic growth agents through their capital formation function (Arshad et al., 2015). To make investment decisions, investors consider exchange rate, interest rate and inflation rate as the key decision variables (Ilahi et al., 2015). It is paramount that investors have knowledge and awareness about the determinants of share prices in order to make optimal investment decisions (Sharif et al., 2015). Governments can formulate policy to stabilize financial markets using research results on the relationship between stock return and macroeconomic variables. Since stock markets are considered a resource mobilization channel, governments can use research results to predict the impact of their policy decisions on the stock market. This will lead to a more stable market and a stable economy in addition to predicting any changes in economic conditions owing to fluctuations in the stock market (Barakat et al., 2016).

Stock prices are reflective of future corporate performance according to economic theory (Amarasinghe, 2015). Endeavors to formulate a country's macroeconomic policies are important and can draw useful insights from studies on the relationship between macroeconomic factors and stock prices or returns. However, past studies on stock price and macroeconomic variables relationships have failed to yield conclusive theoretical positions on this matter as shown in the continuing literature review section which looks at studies in developing, emerging markets and developed markets. Hence, a need to contribute to this debate with a focus on African stock markets is paramount.

In their study on the impact of macroeconomic variables on stock markets with evidence from emerging markets[1] , (Barakat et al., 2016) found out that Inflation, exchange rate and money supply have a positive relationship with EGX30 index whilst interest rate is negatively related to EGX30 index. A positive relationship between exchange rate, money supply, interest rate and TUNINDEX was established. However, unlike for the EGX30, inflation is negatively related to TUNINDEX. In a study by (Eita, 2012) on the influence of macroeconomic factors on stock prices for Namibia, it was found out that an increase in money supply and economic activity (represented by GDP) increased stock prices whilst increases in inflation and interest rates were found to decrease stock prices. It can be concluded that equities for the Tunisian and Namibian bourses are not a hedge against inflation. There is bound to be capital flight towards interest bearing instruments when stock returns become bearish for the Egyptian and Namibian bourses.

Focusing on the relationship between Malaysian stock prices and macroeconomic variables (industrial production, inflation, money supply, interest rate and exchange rate), (Chia and Lim, 2015) found out that Malaysian share prices are influenced positively by money supply and interest rate and negatively by inflation. However, cointegration evidence from the Nairobi Securities Exchange by (Mumo, 2017)suggests a negative equilibrium relationship for money supply and is in agreement to a positive relation for exchange rates and interest rates with stock prices. The novelty of these studies is the attainment of a positive relationship between interest rate and stock prices which is contra to the findings in the afore-mentioned studies.

(Pillaiyan, 2015) investigated the macroeconomic factors influencing Malaysian housing prices using the vector error correction model. Eight macroeconomic variables namely real GDP, bank lending rate, consumer sentiment, business condition,

[1]Egypt (EGX30 Index) and Tunisia(TUNINDEX)

money supply, number of loans approved, stock market (KLSE) and inflation were used for this study. KSLE was found to be the long term major driver of house prices implying that profits gained from investments in stocks are reinvested in residential properties. Other macroeconomic factors found to be significant influencer's of Malaysian housing prices are inflation, money supply and number of residential loans approved. This study was sector specific when compared to (Chia and Lim, 2015) Malaysian index study.

In examining the impact of both exchange rate and oil price fluctuations on the Nigerian Stock market, (Lawal et al., 2016) found both variables to influence share price volatility. This study reports that large shocks in exchange rate and oil prices will increase volatility in the share price. Hence, exchange rate has a positive influence on stock price movements. In another study, the relationship between Nigerian stock market performance and macroeconomic variables was conducted by (Okoro, 2017) with the Ordinary Least Square method used for analysis. Five instrumental variables to explain Nigerian stock price movements namely GDP, money supply, interest rate, inflation and exchange rate were used for this study. The aforementioned variables were able to explain 27.8% of Nigerian stock market performance. GDP, inflation and exchange rate had a positive impact on stock price changes whereas money supply and interest rates had a negative impact. All the five variables do not have a significant impact on stock market performance in Nigeria. The results for the money supply and stock price relationship differ from those for developed markets such as the US as shown in the study by (Bhuiyan and Chowdhury, 2019).

(Ho, 2017) studies the macroeconomic determinants of stock market development in South Africa by focusing at the impact of the banking sector development, economic growth, inflation rate, real interest rate and trade openness on the development of the South African stock market. Long run regression results reveal that the banking sector development and economic growth have significant and positive impact on the South African stock market development whilst inflation and trade openness have a significant negative impact. Interest rate exhibited a negative impact but not significant result. Short run results found economic growth to have a positive impact on stock market development whilst the other macroeconomic variables wielded a negative impact.

(Bilson et al., 2001) examined the influence of selected macroeconomic variables on stock markets for emerging markets. Relevant global and local factors were instrumental in explaining this relationship. Factors considered for this experiment included money supply, inflation, exchange rates, real economic activity, country risk measure, trade sector, interest rates, regional index markets, price to earnings ratio and dividend yields in relation to 27 emerging markets stock prices[2] . As in other studies, exchange rate is clearly the most influential macroeconomic variable with predominant negative signs.

Investors and financial institutions attempt to anticipate expected asset returns upon macroeconomic announcements. In this regard, (Fedorova et al., 2014) examined the impact of macroeconomic announcements on CIVETS (Colombia, Indonesia, Vietnam, Egypt, Turkey and South Africa) stock markets. It was found out that in general macroeconomic announcements affect stock market volatility in CIVETS. Evidence from this study shows existence of information spillovers from the euro

[2]Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico and Venezuela), Asian countries (India, Indonesia, Malaysia, Pakistan, Philippines, South Korea, Taiwan and Thailand), European countries (Greece, Portugal and Turkey), Middle East Country (Jordan) and African Countries (Nigeria and Zimbabwe).

area to Vietnam, Turkey, Egypt and South Africa with respect to stock returns. Egyptian market was considered to be the most integrated with the Euro area and Indonesia was regarded the most segmented market. It was also found that Indonesia did not respond to any euro area macroeconomic news category.

In another study, (Arshad et al., 2015) studied the determinants of share prices of listed commercial banks in Pakistan focusing on internal and external influencing variables. Their research findings revealed that EPS has a positive and significant relationship with share prices. In concurrence with (Barakat et al., 2016), interest rate had a negative relationship with share prices. The book to market ratio had a negative and significant relationship with share prices. In addition, dividend per share was negatively related to share prices, earnings per share had a positive relationship, leverage had a positive but insignificant relation with share prices and GDP had a positive relationship to share prices. A similar study by (Sharif et al., 2015) on the Bahrain stock exchange using eight firm specific variables namely return on equity, book value per share, earnings per share, dividend per share, dividend yield, price earnings, debt to assets, firm size was conducted to understand their impact on stock prices for the Bahrain stock exchange .The ordinary least squares method with robust standard errors, fixed effects and random effects models was adopted for the study. An R2 of o.8 mean that the variation in the stock market of Bahrain was explained by the variables included in this study. Investor knowledge of such information can lead to optimum investment decisions.

Studying the relationship between returns and volatilities of the stock market and macroeconomic fundamentals for the Shanghai Stock Exchange Composite (SSEC) Index in China, (Abbas et al., 2019), employed the Diebold and Yilmaz spill-over index approach under generalized VAR framework to establish the stock price and macroeconomic determinants relationship. The macroeconomic variables used included industrial production, retail sales, terms of trade, hot money, money supply, Treasury bill rate, Treasury bond yield, consumer price index, exchange rate, gold price and crude oil price. The overall returns and volatility spill-over indices show that a higher percentage of the forecast error variance comes from the volatility spill-overs of stock market to macroeconomic variables as compared to return spill-overs.

Also investigating the Chinese markets, (Chen and Chiang, 2016) find out that a better macroeconomic climate and an improvement in liquidity helps in explaining Chinese stock returns. Stock returns were regressed as a linear function of growth in dividends, change in the market level of illiquidity of stocks, change in the macroeconomic climate, US stock returns, change in the international financial stress and the change in exchange rate in natural logarithm. No significant evidence was found to support the view that stock returns can be predicted by the growth of dividend yields. It was also noted in this study that an improvement in the domestic macroeconomic climate was highly significant in explaining stock returns among the other findings.

Using monthly frequency data for the BSE Sensex and inflation rate, money supply, interest rate and exchange rate as macroeconomic variables, (Kotha and Sahu, 2016) explored short and long run relationships between the variables. Granger causality and cointegration tests were run to examine short and long run relationships. Results confirm the presence of a long run relationship between macroeconomic variables and stock prices. An R2 of 11% was attained implying that 11% of the variation in the BSE Sensex is explained by the macroeconomic variables. In addition, interest rate, money supply, exchange rate and inflation have R2 of 6%, 4%, 4% and 6% respectively. Results for this study also report bidirectional causality between exchange rate and Sensex. Inflation, exchange rate and money supply show positive significant relations with stock returns whilst interest rates show negative and insignificant relations with stock returns.

In another study by (Ilahi et al., 2015), inflation rate, exchange rate and interest rate were examined to assess their impact on stock prices for the Karachi stock exchange in Pakistan. A weak relationship between the macroeconomic variables to stock returns was found as exhibited by an R2 of 7%. Therefore, for Pakistan, exchange rate, interest rate and inflation have no association with stock returns; hence foreign investors are free from exchange rate risk. In another study, (Amarasinghe, 2015) examined the causal relationship between interest rates and stock prices for Colombo stock exchange. An R2 of 65.3% was attained in this experiment suggesting that interest rates have an influencing power on stock prices in this market though it is significantly negative. Interest rates were also found to Granger cause stock prices and the relationship is unidirectional.

A review of the impact of both micro and macro variables on the Turkish banking stock prices was examined by (Rjoub et al., 2017). An OLS was run and included the following variables both at micro and macro; capital adequacy, asset quality, management quality, earning, liquidity, size, inflation, exchange rate, industrial production, interest and money supply. Capital adequacy and liquidity were found insignificant in influencing stock prices whilst the remaining micro variables were found to be positive and significantly related to stock prices. With regards to the macroeconomic variables, money supply was found to be positive and statistically significant, interest rates to be negative and statistically significant and industrial production, positive but not statistically significant. Exchange rate is negatively related to stock prices and inflation is positively related to stock prices. Both exchange rate and inflation are reported to be not statistically significant. In addition, bidirectional causality was found between asset quality, bank size, money supply and bank stock prices.

Another experiment by (Islam et al., 2017) attempted to establish macroeconomic and institutional determinants of capital market performance in Bangladesh with focus on the Dhaka stock exchange. Institutional and macroeconomic variables (total market capitalization, CPI and GDP) were found to be significant influencers of capital market performance. In pursuit to establish some European evidence on stock prices and macroeconomic factors, (Peiro, 2016) analysed the dependence of stock prices on macroeconomic variables in France, Germany and the United Kingdom. Industrial production, interest rates and share prices were used for this study. Annual returns were regressed on several lags of annual changes in interest rates and industrial production and results were insignificant. In other words, these economic variables do not allow anticipation of the evolution of stock markets. Industrial production was however noted to be the important factor to explain stock price changes. The changes in future production positively affect stock prices whilst a negative effect is found for interest rates.

(Paul and Malik, 2003)looked at macroeconomic factors and bank and finance stock prices in Australia. The share index was explained by movements in inflation rate, interest rate and real GDP. The three macroeconomic variables are cointegrated with stock prices. Interest rate has a negative effect, while GDP has a positive effect on stock prices and inflation was found to have no significant effect on stock prices.

Taking a different approach from most researchers, (Bhuiyan and Chowdhury, 2019) looked at macroeconomic variables and stock market indices focusing on sector indices other than composite indices. The macroeconomic variables considered for this experiment included money supply, interest rate and real economic activity. Sectoral indices included energy, financials, consumer discretionary, consumer staples, real estate, health care, industrials, materials, utilities and technology. Their paper concluded that a long term relationship between macroeconomic variables and the S&P500 for the US and TSX for Canada. In the US, macroeconomic variables were reported to influence the composite and sectoral stocks clearly with money supply influencing stock positively whilst interest rates influenced negatively. However for Canada, the cointegration tests could not find any clear link between macroeconomic variables and stock market indices. Also key in the research findings is that industrial production is noted as an unreliable indicator to explain stock price movements due the fact that the US economy has transformed from a manufacturing based economy into a service based economy. These findings contrast the study results for (Peiro, 2016) who argued for the importance of industrial production in explaining stock price movements.

(Gay, 2016) studied the effects of macroeconomic variables on stock returns for four emerging economies namely Brazil, Russia, India and China (BRIC countries). The study looked at the impact of exchange rate and oil prices on stock prices. A positive relationship between exchange rate and stock index was found for Brazil, Russia and China. An inverse relationship between stock prices and oil prices was noted. Overall, the effect of international macroeconomic factors of exchange rate and oil price on the BRIC markets did not reveal a significant relationship. This could have been a result that other international and domestic macroeconomic variables (such as production, inflation, dividend yield etc) could be at play influencing stock market prices.

With a focus on the Dow Jones stock market in USA, GDP, CPI, industrial production, unemployment rate and long term interest rates were used to examine the relationship between stock prices and macroeconomic variables (Jareno and Negrut, 2016). Positive relationships were noted for GDP, Industrial production, CPI whilst a negative relationship for interest rates and unemployment rates to US stock prices was noted. From the preceding debates, it can be noted that mixed results for stock price influencing variables are existent. Stock price and macroeconomic variable relationship debates have failed to yield conclusive theoretical positions regarding their link. There are various macroeconomic factors that are found to influence the share price including exchange rates, money supply, interest rates and inflation. There exist theories to explain the relationship between stock price and returns with macroeconomic variables.

With regards to the stock price and exchange relationship, two common theories to explain this relationship are the “flow-oriented” model (Dornbusch and Fisher, 1980; Gavin, 1989) and the “stock-oriented” model (Branson, 1983; Frankel, 1983).Also known as the goods markets approach, “flow-oriented” models of exchange rate determination postulate that exchange rate movements affect international competitiveness and the trade balance of an economy. This subsequently influences the output levels of firms in that country and thus in turn affects current and future cash flows of companies and their stock prices (Chen and Chen, 2012). Stock market share price movements have an effect on aggregate demand through wealth, liquidity effects and, indirectly, the exchange rate.

Local investor wealth and demand for money is reduced as a result of stock price reduction, hence results in subsequent implications for currency depreciation according to the monetarist models of exchange rate determination (Adjasi et al., 2011). (Bodnar and Gentry, 1993) believed that exchange rate fluctuations can substantially influence firm values as a result of the following changes: terms of competition changes, input price changes and foreign currency denominated asset value changes.

In addition, the portfolio balance models/"Flow oriented" model (Dornbusch and Fisher, 1980), suggests that there is a negative relationship between exchange rates and stock prices and that causation is from stock prices to exchange rates. Under such a model, market players hold both domestic and foreign assets whereby exchange rates play a key role of balancing demand for and supply of assets. If stock prices increase, this results in an increased demand for domestic products whilst shedding or selling off foreign assets thus causing a local currency appreciation. However, domestic currency depreciation will make local firms more competitive leading to an increase in their exports, thus making their stock prices go up. Such a scenario is best explained by a positive relationship with causation running from stock prices to exchange rate.

In the asset market model/"stock-oriented" model, exchange rates just like any other asset prices are determined by the expected future exchange rates. Any news that affect future values of exchange rate will affect today's exchange rate. However, with this approach, there is notably a weak or no association between stock prices and exchange rates. Hence, this makes the theoretical explanations to this relationship inconclusive, a gap this research seeks to address by providing further evidence to the said matter.

Inflation is another important macroeconomic variable believed to be related to stock prices, and in turn, also affected by it (Gupta and Inglesi-Lotz, 2012). Inflation can either have a positive or negative effect on stock prices. In consideration of the dividend growth model (Gordon, 1962), stock prices are directly related to current and expected growth rates of dividend returns and inversely related to the required rate of return on the equity.

Premised on the aforementioned growth model, inflation exhibits a positive impact on stock prices through two ways: to start with, a monetary easing that stimulates the economy along with inflation would have a positive impact on the growth rate of dividends. Secondly, a monetary expansion that depresses bond returns would result in an increased demand for equities, which in turn, would cause the average investor to lower expected rate of returns of equities. Whether it is increased dividend returns or decreased expected returns on investment, both serve to raise stock prices.

There is also a possibility of inflation leading to lower stock returns. Sustained increases in inflation reduce real stock prices since the tax code exerts a distortionary effect between depreciation costs and capital gains (Feldstein, 1980). In addition, the Proxy Effect Hypothesis (PEH) by (Fama, 1981) postulates that a negative correlation between stock prices and inflation is induced by a positive relationship between stock returns and expected economic activity (as proxied by inflation) and an inverse relationship between expected economic activity and inflation.

Finally, as pointed out by (Sargent, 1999), and (Cogley and Sargent, 2001), if the monetary authority, under the assumption of an exploitable trade-off between inflation and unemployment, succumbs to the temptation to inflate (until time-consistent inflation rates are achieved), the resulting higher expectations of inflation would increase long-term rates leading investors to more aggressively discount future dividends (Valcarcel, 2012). At the same time, the subsequent contractionary monetary policy actions could also contribute to lower stock returns due to the slowing down of economic activity and, thus, depressing current and expected future earnings (Valcarcel, 2012)).

Hence, theoretically, inflation can either increase or decrease stock prices. At the same time, real stock price movements can affect the inflation rate through the wealth-effect, i.e., via its impact on consumption and hence aggregate demand. (Ludwig and Slok, 2004)and more recently (Simo-Kengne et al., 2015)discuss four different channels of influence for stock prices on consumption: First, the realized wealth effect implies that an increase in stock prices exerts a direct positive effect on stockholders' consumption as a consequence of the realized gain. Second, the unrealized wealth effect refers to the increase in consumption spending based on the expectation that raising the current stock price will result in higher future income and wealth. Third, the liquidity constraint effect implies that increasing stock prices raise the value of collateral against which financially constrained households may borrow to increase their consumption. Fourth, the stock option value effect, implies that an increase in stock prices leads to the increase in the value of stockholders' options which may translate into higher consumption irrespective of whether the gains are realized or unrealized. In other dwords, real stock prices and inflation are likely to be positively related through the wealth effect.

With regards to the stock price and money supply relationship, the Quantity Theory of Money posits that an increase in the money supply results in a change in the equilibrium position of money with respect to other assets, including equity shares, in the portfolio balance of asset holders (Dhakal et al., 1993). An increase in the money supply is expected to create excess supply of money balances and in turn, excess demand for shares. Thus, share prices are expected to rise.

Key to forecasting stock prices is the ability to pick the most influencing predictor variables. Various variables have been noted to affect stock price, however there is no consensus on which the most influencing variables are (Altinbas and Biskin, 2015). Given the afore-mentioned debates on stock price and macroeconomic variable debates, the following results are expected to be achieved for the African stock markets under consideration in this research;

TABLE 3.1: Expected Stock Price and Macroeconomic Variable Relationships for African Stock Markets.

Exchange Rates	**Interest Rates**	**Money Supply**	**Inflation**
Positive	Negative	Positive	Negative

Source: Own preparation based on Barakat et al., (2016), Lawal et al.,(2016), Eita(2012), Chia and Lim (2015)

Guided by the preceding literature review , this study tested eight hypotheses to ascertain the relationship between closing index price (dependent variable) and inflation, interest rate, exchange rate, money supply (independent variables) as follows;

H1: Inflation does not affect index closing stock price in the long run.

H2: There is no causal relationship between inflation and index closing stock price.

H3: Interest rate does not affect index closing stock price in the long run.

H4: There is no causal relationship between interest rate and index closing stock price.

H5: Exchange rate does not affect index closing stock price in the long run.

H6: There is no causal relationship between exchange rate and index closing stock price.

H7: Money supply does not affect index closing stock price in the long run.

H8: there is no causal relationship between money supply and index closing stock price.

In addition to the macroeconomic variables responsible for stock price movements, there are other factors that can explain stock price movement but at a microstructure level.

3.4.2 Microstructure Structure Variables Influencing Stock Price Movements

Market microstructure models were introduced to describe the dynamic behaviour of an asset price whose motion is considered to be driven by the excess demand and liquidity of the market (Xi et al., 2016). For a long time, market microstructure has been considered to influence asset pricing (Ormos and Timotity, 2016). Microstructure in equity offering decisions includes the price discovery function. Higher market liquidity raises trades among liquidity and informed traders, thus facilitating price discovery (Cheung et al., 2016).

Informed traders play a crucial role in price formation in financial markets. In microstructure models, informed traders receive a private signal about the security's value and build positions before information is widely available. The activities of informed traders will thus influence the informational efficiency of prices before news releases (Baruch et al., 2017). Microstructure models predict that stock prices incorporate more information when informed agents use aggressive orders before news releases.

Various market microstructures are responsible for asset pricing. Two key factors that influence the price discovery process are the price adjustment process and trading noise (Amihud and Mendelson, 1989). Factor number one looks at the speed of adjustment of market prices to new information whilst the second factor pertains to transitory price fluctuations generated by friction in the trading process. Other factors such as a stock market's clearance, settlement, depository (CSD) facilities and auction principles for price discover are also crucial in the debates on price formation (Xu, 2000).

An understanding of order imbalances, liquidity, transaction costs, trading volumes, trade counts and trade sizes is important in the price discovery function of stock markets (Kyle et al., 2019; Wang et al., 2019). In addition, market efficiency is affected by several characteristics of individual stocks such as market capitalisation, price volatility, trading volume, institutional trading and trading costs such as information asymmetry and illiquidity (Hu and Prigent, 2019). A consideration of these market microstructures is considered to explain the predicted prices in this current research.

3.5 Stock Market Prediction Models and their Performance in Nonlinear Dynamic Environments

3.5.1 Statistical Approaches to Stock Price Prediction

In the past, researchers adopted the conventional analysis methods when constructing models to predict stock price trends and used techniques such as multiple regression analysis model (Fama and French, 1993) or time series model such as ARMA and ARIMA (Kendall, 1990). The disadvantage with these two models is that they can only be applied to linear problems and are very poor in forecasting nonlinear problems and with multi-collinearity issues.

Based on the fact that statistical approaches, traditional methods of time series forecasting have failed to completely and satisfactorily predict financial time series mainly because of the nonlinear nature of financial time series (Reid et al., 2014), caution must be taken to note that at times neural models may be superceded by some linear models in stock price prediction (Shan et al., 2015). It is therefore not a given that ANNs will always outperform traditional time series techniques. This research also compared a more recent traditional statistical machine learning architecture named GAM to ANN architectures, since it can model nonlinear patterns and assess the notion of ANN superiority to statistical approaches.

3.5.2 Artificial Neural Networks for stock Price Prediction

Weaknesses of statistical techniques paved way for the establishment of neural networks that work well in nonlinear problems to take centre stage. Most researches have concluded that ANNs outperform traditional linear models in time series prediction (Abdelmouez et al., 2007; Egeli et al., 2003; Altay and Satman, 2005; Avci, 2007; Kumar and Thenmozhi, 2009; Senol and Ozturan, 2008). Neuro-computational models are expected to surpass traditional statistical techniques such as regression and ARIMA in predicting stock exchange price changes because of their robustness and flexibility of modelling algorithms (Liang et al., 2011). With changes in computational capacity, a switch to ANN architecture is an ongoing exercise with a motive to increasing prediction capacity. New and better ANN prediction models are being developed.

Increased use of ANNs in time series as well as their satisfactory performance compared to other approaches has been noted in literature (Cai et al., 2013; Tsai and Chiou, 2009). In comparative studies between conventional quantitative methods and ANNs, it was found that ANNs consistently outperform conventional financial models (Desai and Bharati, 1998). In addition, ANN models outperform corresponding linear models (Cao et al., 2011). The application effect of traditional technical analysis methods may not be satisfactory in most times (Lu, 2010), hence the increased use by investors of techniques such as ANNs, which have better prediction precision (Zadeh, 1994). A growing body of literature exists that outlines the better performance of ANNs in comparison with statistical models for time series prediction (Hill et al., 1994). ANNs have been successfully applied for nonlinear modelling of time series (Ferreira et al., 2008).

3.5.3 Predicting using Machine Learning Techniques

Closing Stock Price Prediction

There are various machine learning techniques that are used to predict the share price. (Hafezi et al., 2015) developed a four layered architecture bat neural network multi agent system (BNNMAS) to predict stock prices for 17 Germany national stock indices and 3 international indices using quarterly data for 32.5 years. Using MAPE, the proposed method was compared to Genetic ANNs (GANN), Generalized Regression Neural Network (GRNN) and Exact Radial Basis Network (ERBN). The proposed model BNNMAS outperforms all models by having the smallest MAPE of 2.84, implying much greater profit from this model. Also basing their study on the MAPE metric, (Laboissiere et al., 2015) proposed an ANN model that uses the Levenberg –Marquart Algorithm to estimate minimum and maximum Brazilian power distribution companies stock prices for a six year period. MAPE results for maximum and minimum day stock prices were lower than 0.9% and 2.1% respectively.

In pursuit of perfect financial price time series prediction for the Shangai Stock Exchange Composite index (SSE), (Wang and Wang, 2015) designed a method that integrates PCA into a stochastic time strength neural network (STNN) and called it the PCA-STNN model to forecast stock prices on the Shanghai Stock Exchange Composite Index –SSE; Hong Kong Hang Seng 300 Index –HS300; Dow Jones Industrial Average Index –DJIA and Standards and Poor's 500 Index –S&P 500. Daily data for the 4 indices was for 6 years for all the other indices except HS300 which had data spanning for 8 years. This proposed model was compared to BPNN, PCA-BPNN, STNN and SVM; the PCA-STNN displayed a much better performance than its comparatives based on the MAE, RMSE and MAPE metrics. However, the study could not explain why the algorithms behaved differently in the various markets, a gap that this current research is thrust upon.

In a different study, (Bisoi and Dash, 2014) proposed a simple infinite impulse response (IIR) filter based dynamic neural network and an innovative optimized adaptive unscented Kalman filter to forecast daily stock prices in 4 Indian stock markets (Bombay Stock Exchange, IBM stock market, Reliance stock market and Oracle stock market). Daily data for 4 years are used for the experiment. The proposed hybrid model of unscented Kalman filter and differential evolution (DEUKF) outperformed other learning strategies by having the lowest MAPE of about 2%.

In addition, (Dash et al., 2015) also proposed a differential harmony search-based hybrid interval type2 -CEFLANN - fuzzy EGARCH model for stock volatility prediction. Daily closing price data for one year for the BSE Sensex and CNX Nifty index for the Indian stock markets were used and evaluated on the following metrics namely: Mean Squared Forecast Error (MSFE); Root mean Squared Forecast error (RMSFE); Mean absolute Forecast error (MAFE) and Relative Mean Absolute Error (RelMAE). The proposed model is compared to GARCH (1, 1), GJR-GARCH (1, 1). EGARCH (1,1), type1 Fuzzy EGARCH (1, 1), type1 fuzzy CE-EGARCH (1, 1) and ITF2-EGARCH (1, 1) models. Results from this experiment reveal that the proposed model using Gaussian function with uncertain variance and fixed mean offers significant improvements in forecasting performance compared to all other volatility models.

(Dash et al., 2014a) explored the performance of two single hidden layer feed forward neural networks namely Radial Basis Function (RBF) and a low complexity functional link artificial neural network (CEFLANN) on five major stock indices namely: BSE SenSex and CNX Nifty from India, FTSE 100, Nikkei 225, and SP 500 from UK, Japan and USA respectively over a three-year period using daily closing prices. The proposed models were compared to the Self Adaptive Differential Harmony Search Based Optimised Extreme Learning Machine (SADHS-OELM), DE-OELM, SADHS, SGHS, HS, DE, ELM and BP for one day ahead closing price and volatility forecasts. The RMSE and MAPE are used for performance comparisons for closing price predictions and MSFE, RMSFE and MAFE are used for performance comparison of volatility forecasts. Computational results from this study revealed that the CEFLANN model learned using SADHS-OELM proved to be the better forecasting tool for closing price and volatility forecasts. Using a different approach, (Mohapatra et al., 2012) applied the Differential Evolutionary based Functional Link ANN (DE based FLANN) to the Indian Stock Market (BSE), INFY and NSE Nifty with the DE based FLANN proving to be a superior prediction model.

An ANFIS is a hybrid technique that integrates the advantages of learning in an ANN and using a set of fuzzy if-then rules with appropriate membership functions to generate input–output pairs with a high degree of accuracy. (Wei, 2016) developed a hybrid ANFIS model based on empirical mode decomposition for stock time series forecasting for the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and the Hang Seng Stock Index (HSI) over 7 years and 5 years respectively. The RMSE metric was used to evaluate performance of this model in comparison to Chen's Model, Yu's model, the Autoregressive (AR) model and the Support Vector Regression (SVR) model. The model outperformed all the other models as it had the lowest RMSE for both indices. The most important contributory factor of this model is the inclusion of the empirical mode decomposition (EMD) to obtain interpretable information on the input variable. EMD offers a new approach by which the non-stationary and nonlinear behaviour of time series can be decomposed into a series of valuable independent time resolutions and can reveal the hidden patterns of time series.

Also with a focus on the TAIEX, (Chen and Lee, 2015)used daily data from the NASDAQ, DJIA and TAIEX over a 6-year period. They proposed a weighted Least Squares Support Vector Machine (LS-SVM) based learning system to forecast these markets. This model is compared to alternative models and evaluated based on the MAE, MSE, RMSE and MAPE and its forecasting ability is superior to all other models. No explanation was proffered for why the LS-SVM outperformed all other models. In another TAIEX experiment through the adaptation of the hybrid approach to forecasting, (Hsu, 2011) developed a self-organizing map neural network fused with genetic programming to come up with the SOM-GP hybrid for stock price prediction of finance and insurance sub index of the Taiwan Stock Exchange. Daily data for thirteen years were used and 16 technical indicators were extracted from the data and used as inputs to the study. The experiment results revealed that RMSE, MAE and MAPE were 19.44, 14.20 and 1.44 X $10^{-}2respectively$.

In several studies, technical indicators were used inclusive of the opening price, high, low and closing prices as well as volumes traded amongst some other technical variables. Working with 7 technical indicators , a database of 34 countries' stock market indices over a 6 year period, (Hsu et al., 2016) compared ML techniques to econometric method based models on five experimental factors namely; market maturity, model simulation technology, forecast horizon, covariate composition and prediction method. Most high-income markets produced high profitability whilst in middle income markets, ROI was low. Another major finding was that little value on informational content is reported with regards to use of recent price information and technical inputs. Markets have a long-term memory and not much is learnt from the most recent price input data.

In addition, working with daily stock data and 6 technical indicators chosen using a general search of literature as inputs, (Ticknor, 2013) proposed a Bayesian regularized ANN to predict the next day's closing price for Goldman Sachs Group, Inc and Microsoft Corp. Daily data was for a period of 3 years and the ANN proposed in this study was a three-layer ANN with the input, hidden and output layers. MAPE was used as the performance evaluation metric for this study. MAPE results for Goldman and Microsoft were 1.0561 and 1.3291 respectively.Working with a database from the Nikkei 225 index for a period of almost 20 years, (Qui et al., 2016) collected 71 financial variables which were a composite of financial indicators and macroeconomic data to set up an ANN model for predicting stock price returns in this stock market. Fuzzy surfaces were used to select the optimal input variables as a feature selection tool and only 18 out of the 71 variables were chosen as input in this study. The constructed BPNN was compared to optimized BPNN which are GA-BPNN and SA-BPNN. Genetic Algorithms and Simulated Annealing are global search techniques. It was found out that the GA-BPNN model performs much better than all the other models in this study. This study only focused on stock market return prediction.

Using another novel approach of Increasing Decreasing Linear Neuron (IDLN), (Araujo et al., 2015) performed stock price prediction exercise with the model being compared to ARIMA (statistical model), MLP (ANN model), IMP (morphological NN model) and a SHIF (hybrid model). Data for this experiment were obtained from Banco do Brasil SA (BBAS3), Brasil Foods SA (BRFS3) and BR Malls Participacoes SA (BRML3) counters on the Brazilian Stock Exchange. Findings from this experiment revealed a reliable better performance of the proposed model to its alternates.

Other prediction techniques regards closing stock price prediction have been implemented. A new model to predict stock price returns on the behaviour of analyst's recommendations and Bayesian rule are proposed for the Chinese stock markets (Duan et al., 2013). Two year's daily extracted data were used for the experiment. This fusion approach combined historical prices and analyst recommendation history. It was noted that maximum accuracy between 84.35% and 94.2% was achieved in this study. This model outperformed its comparatives namely ANNs and HMMs.

(Suzuki and Ohkura, 2016) improved classical technical analysis for stock price prediction to enable it to detect investment timings quickly. They proposed financial technical indicator based on chaotic bagging predictors for adaptive stock selection in the Japanese and American markets over a twenty-three-year period. A chaos prediction model was developed with use of two new technical indicators [spatial technical discriminant analysis (STDA) and spatial relative strength index (SRSI)] based on the nonlinear dynamic theory. Investment performance is evaluated using the asset growth rate, the maximum draw-down rate, the profit factor and the winning rate. It was noted that the chaotic prediction increased the number of investments by substituting spatial neighbours for temporal historic data and improved the learning ability of complex behavioural patterns hidden in financial markets.

Experience with artificial intelligence applications to stock market prediction has pointed towards a multi-strategy approach to discovery and prediction (Chun and Park, 2005). Working with this concept in mind, (Chun and Park, 2005) developed a dynamic ensemble case based reasoning (DAE CBR) model to forecast daily stock prices of the Korean Stock Price Index (KOPSI) using daily data for four and a half years (4.5 years). In pursuit of pre-processing the data and making it possible to work with, a log transformation was done to standardize the data. Thereafter it was differenced and standardized. Results from this experiment show that DAE CBR is significantly better than the random walk model at level $p<0.01$ and that DAE CBR outperforms all other models though it failed to outperform other models statistically significant because the experiment was performed using the hit ratio and not MAPE.

Compared to other studies that are mostly centred on the EMH, (Taveeapiradeecharoen et al., 2014) developed a stock price prediction model based on the Extreme Value Theory and Belief Function Theory. Daily data for the IRPC counter in the stock exchange of Thailand for a period of 11 years were used for this study. It was found out that in the next 15 years, the maximum return of IRPC will not exceed 3.5035% based on the Generalized Extreme Value Distribution (GEV).

MLP models though one of the earliest model architectures, are still very important prediction model architectures. Using a MLP with varying hidden nodes trained with either a gradient descent (GD) or Broyden- Fletcher-Goldfarb-Shanno (BFGS) activation function on the Romanian Stock Market, (Ruxanda and Badea, 2014) showed that the lowest error is achieved by the model MLP 3-4-1 BFGS 7 T which uses a BFGS training algorithm, 4 hidden nodes and hyperbolic tangent function in the hidden layer. A replicative study was also conducted on the Croatian Stock Market by the same authors and it was still found that a BFGS learning algorithm is a much better option to modelling volatile stock market data. In another study by (Olatunji et al., 2013), it was found out that MLP achieves a correlation coefficient in the Saudi Arabia Stock Market.

(Mieko and Seiji, 2007) used 8 stocks from the New York Stock exchange to predict intra-day stock prices. They used the technical analysis approach. In that regard, they extracted 10 technical indicators broadly categorized into three classes namely trend type, oscillator type and momentum type indicator categories. A genetic approach was instituted to discover the best combination for each stock under various conditions adaptively. General findings from this research include the facts that the optimal combination of indicators perform well; indicators related to moving averages are effective and that MACD or RSI are not very good on their own and need to be combined with other trend type indicators to be very effective. Average predictions were high as 81% and 77% for IBM and GM.

The above is empirical evidence on closing stock price predictions for developed and developing stock markets. However, empirical evidence for emerging and frontier African stock market prediction are scanty, a gap that this current research embarked on. Secondly, though they are varying prediction models, none of the studies tested the useful of deep neural networks for closing price prediction, another gap that this research attempts to close. It is the intent of this study to develop a prediction model that can maximise financial returns to investors. Third, most of the experiments were comparative in nature. However, no plausible explanations were given as to why the same models performed differently in various markets. The next section looks at market direction related predictions.

Market Direction Prediction

(Oliveira et al., 2013)developed an artificial neural network (ANN) to forecast stock price and improvement of the directional prediction index of the PETR4. A total of 15 technical and 11 fundamental variables were used as input for the study. The experiment used monthly data over 12 years and measured performance using four metrics namely, MAPE, RMSE, THEIL and POCID. Window size 3 gave the best results, with the POCID index of correct prediction being 93.62% and 87.50% for the test and validation set respectively.

Focusing on the Shanghai Stock Exchange (SSE), with an endeavour to improve forecasting ability, (Yu et al., 2014) developed a hybrid model between SVM and PCA to forecast closing price of the SSE using data for two years. The SVM-PCA model outperformed comparative models by achieving an accuracy of 75.4464% and 61.7925% in both the training and test sets respectively. Taking a different approach to stock prediction, (Fenghua et al., 2014) developed a stock prediction model based on the singular spectrum analysis (SSA) in order to decompose stock prices series into terms of the trend, market fluctuation and noise. The study made use of five years closing data of the SSE and used MSE, MAPE, Directional Symmetry (DS) and Correlation coefficient as performance measures. This technique was compared to Ensemble Empirical mode Decomposition (EEMD)-SVM and single SVM models. It was noted from the experiments that SSA-SVM gave better predictions as compared to all other models. SSA-SVM was able to capture the features of the original index series much better when compared to EEMD-SVM and SVM with MSE, MAPE, DS and R at 0.001785, 0.007245, 67.979% and 97.343%. Empirical evidence from this research suggests that ensembles are not all the time better performers than single models.

Using 3-year daily data for five stock market indices namely: the Financial Times Stock Exchange 100 index (FTSE), Hong Kong Hang Seng Index (HSI), Japan Nikkei Index (NIKKEI), China Stock Exchange Component Index (SZI) and USA Dow Jones Industrial Average Index (DJIA), (Ng et al., 2014) proposed a new weighted localised Generalization error (wl-GEM) model. Seventeen (17) technical indicators were used for this study. Results reveal that a trader who uses this technique will make 91.89%, 29.67% and 9.16% of positive rates of return in HSI, FTSE and DJIA respectively. No explanation was given to why the model performs well in HSI and poorly for the DJIA.

In a study by (Kim and Han, 2016), a classical approach built on ensemble learning and bootstrapping to predict stock price movements (up and down) for the Korea Composite Stock Price Index (KOPSI) was done. The model was compared to the original model based on the degree of change as a performance measure metric. Inclusion of technical indexes and commodities were suggested to better the model and could be incorporated in future experiments. In another experiment, (Zhong and Enke, 2017) predicted the daily direction of the closing price of the SPDR S P 500 EFT and found that the PCA-ANN outperforms the other models in terms of accuracy, p-values and risk adjusted profits.

Taking a different approach, (Wang and Wang, 2015) proposed a new model structure to predict stock market trend changes which used a dynamical Bayesian factor graph. In their model structure, three key steps were adopted. To start with was the selection of a set of macroeconomic variables as the initial set of factors. Following this was the construction of the dynamical Bayesian factor graph displaying the connecting topology of the most dominant factors in that network over a period of time. Lastly, identification of drastic topological change over a few time adjacent graphs was done. An application of this proposed method was done over 11 years for the Shenzhen stock market and SP 500 in China and the USA respectively. A set of nine initial factors were selected for the experiment using the Adaptation algorithm. Resulting factor relationships for the US Market were noted to be significantly different from its Chinese counterpart.

(Lee, 2009) proposed a hybrid feature selection method namely: F-Score and Supported Sequential Forward Search (F-SSFS). This hybrid is a combination of filter and wrapper methods for optimal feature subset selection from the original feature set. This method was compared to the BPNN along with three feature selection methods including Information Gain, Symmetrical Uncertainty and Correlation based feature selection through paired t-test. This experiment was set to predict the direction of change in the daily NASDAQ index using data that spans over 6 years and use of 29 technical indicators. In order to estimate the relative contributions of the input features, the Garson's (1991) index was used. SVM achieves a remarkable average accuracy level of 85.4% while BPNN achieves an average accuracy of 71.5%.

In addition, (Patel and Marwala, 2006) also took a novel approach forecasting the JSE All Share Index, NASDAQ 100, Nikkei 225 and Dow Jones Industrial Average (DJIA) Stock exchanges where they modelled a MLP compared to RBF. The highest accuracy level was achieved in the DJIA and the lowest accuracy level recorded in the Nikkei 225 at 72% and 64% respectively with the JSE and NASDAQ having 70.4% and 69% accuracy levels. In a different study by (Carpinteiro et al., 2012), the MLP was compared to the SVM and Hierarchical Models (HM) on the Brazilian Stock Market Fund and the HM was found to be better than SVM and even much better than MLP.

(Kara et al., 2011) proposed ANN and SVM to predict the stock price index movement of the Istanbul Stock Exchange. Ten technical indicators selected through a review of domain experts and prior researches were used as inputs in this study which used data for 11 years. It was noted that the average performance of the three-layered ANN model was significantly better compared to the SVM with ANN and SVM having 75.74% and 71.52% respectively. This is one of the few studies where ANNs outperform SVMs.

(Tsai et al., 2011) proposed classifier ensembles to predict stock using four years' quarterly data for the Taiwan stock market. A total of 30 financial ratios and economic indicators were selected for the study. Three common classifier ensembles namely: multilayer perceptron (MLP); classification and regression tree (CART) and logistic regression (LR) were used for the experiment. Results reveal that the LR model outperformed the other models in terms of average accuracy, whilst the MLP performed better when predicting positive returns and the LR when predicting negative returns. In this experiment, it was noted that classifier ensembles perform better than single classifiers.

Through combining technical analysis to nearest neighbour classification, (Texeira and Oloveira, 2010) proposed this hybrid model to predict daily closing prices for 15 stocks from the Sao Paulo Stock Exchange (Bovespa) using daily data for 11 years. The proposed method was compared to the buy and hold strategy. Out of the 15 stocks, results show that the proposed method performs better for 12 of the 15 stocks when compared to the buy and hold strategy. Hybrid models tend to increase prediction performance.

Using 10 years of stock price data from CNX Nifty and SP BSE Sensex, (Patel et al., 2015a) conducted a study to compare the prediction performance of ANN, SVR, Random Forest and Naive Bayes algorithms for a task of predicting stock price co-movements. Accuracy levels of 86.69%, 89.33%, 89.98% and 90.19% were attained for ANN, SVM, Random Forest and Naive –Bayes respectively when using trend deterministic data. One key lesson for machine learning based stock predictions is that increased accuracy is possible if pre-processed data are used. A rising approach to stock price prediction is that two stage architectures in financial forecasting achieve higher performance as compared to individual architectures (Wang et al., 2016). This convention was adopted in a study by (Kumar et al., 2016) where they compared RF-PSVM, RR-PSVM, LC-PSVM and RC-PSVM models. The Proximal Support Vector Machine (PSVM) was hybridized to different feature selection techniques namely; Linear Correlation (LC), Regression Relief (RR), Rank Correlation (RC) and Random Forest (RF). Fifty–five (55) technical indicators were selected for this study with data being sourced from twelve (12) stock market indices for a 6-year period ranging from January 2008 to December 2013. The highest accuracy rate achieved was for the CNX Nifty at 62.72%. It was found that nine out of the twelve stock indices that achieved the highest accuracy levels used RF-PSVM model. It can be noted that the hybrid models in this (Kumar et al., 2016)study did not improve on prediction accuracy as compared to single models in the (Patel et al., 2015a) study.

With the use of daily closing prices for 7 stock indices namely BSE, DJIA, TAIEX, NASDAQ, SP 500, FTSE and LSE and 15 years trading data, (Nayak et al., 2015) proposed an Artificial Chemical Reaction Optimisation Neural Network (ACRNN) for stock market prediction. This ACRNN model is compared to MLP, MLR and RBFNN models. Future projections are done one day ahead, one week ahead and one month ahead. In all three scenarios, the ACRNN outperformed all other models in terms of reduced error rate, gain in accuracy and gain in POCID. A POCID value of 93.3% for the TAIEX market was achieved.

Trading Strategy Models for Stock Prediction

(Dash and Dash, 2016) introduced a novel approach that combines technical factors derived from past historical prices to a trading system that classifies stock market movements either as up, down or hold. The successful classification of up and down movements in stock price index values is not only beneficial to investors but also to policy makers for them to monitor the market. The novelty of this research rests on a decision support system using computational efficient functional link artificial neural network (CEFLANN) with ELM learning approach and a set of rules based on technical analysis to generate the trading decisions more effectively. This CEFLANN model was compared to other soft computing methods such as SVM, Naive Bayesian and Decision Trees, and it was found out that the proposed model consistently generates the highest profit among the others. This finding show that better hybrid models can be implemented which outperform the generally best SVM models.

(Gocken et al., 2016) constructed GA-ANN (ANN hybridized with Genetic Algorithm) and HS-ANN (ANN hybridized with Harmony Search) models for stock price prediction with GA and HS used as feature selection techniques of the most important indicators. Daily data from the BIST 100 index in Turkey for a period of 8 years 3 months was used for the study. A total of nine various loss functions[3] were used to measure performance of this experiments. It was noted that the HS-ANN model outperformed all the other forecasting models with regards to all statistical loss functions. Overall error rates with regards to the MAPE statistic is 3.38,3.86 and 3.8 for the HS-ANN, GA-ANN and ANN models respectively. With regards to profitability, HS-ANN yields a return of 6.04% while the GA-ANN model returns only 1.12% profit.

In another study, (Nayak et al., 2016) built models to make one day and one month ahead predictions based on past historical prices and sentiment from social media data from the year 2003 to 2015. The study was directional orientated looking at possible up and down movements of closing price. Very interesting results which came from this study are that for the three companies used (bank, mining and oil), decision boosted trees followed by logistic regression had better accuracy levels compared to SVMs. These findings are unique in that most studies found SVMs to be the best prediction model but in this study, SVMs were outperformed by Boosted Decision Trees and Logistic Regression.

Driven by a goal of constructing a model that can predict short term trends on the stock market which can lead to a profitable trading strategy, (Zbikowski, 2015) used volume weighted SVM with walk forward testing and feature selection to develop his prediction model. He used 6 technical indicators derived from daily OHLC (Open, High, Low and Closing) prices over an 11-year period for the S&P 500 and implemented the Fishers Feature selection method. Due to use of delays for technical indicators and enlargement of the training set, better results were attained in terms of rate of return and maximum drawdown.

In order to improve the classification accuracy, ensemble learning which has an ability to create several classifiers and making decisions by combining their classification results is becoming a prediction model of choice. (Mabu et al., 2015)developed an ensemble learning of rule based evolutionary algorithm using multi-layer

[3]Mean Absolute Error (MAE); Mean Square Error (MSE); Root MSE (RMSE); Mean Absolute Relative Error (MARE); Mean Squared Relative Error (MSRE); Root Mean Squared Relative Error (RMSRE); Mean Absolute Percentage Error (MAPE); Mean Squared Percentage Error (MSPE); Root Mean Squared Percentage Error(RMSPE)

perceptron (MLP) for supporting decisions in stock trading problems. In this model, large numbers of stock trading rules which combine technical indices are extracted using a graph based evolutionary algorithm called Genetic Network Programming with reinforced learning (GNP-RL). A sum of 9 technical indicators is used for the experiment over a 5-year period using data on the Tokyo Stock Exchange in Japan. Comparisons are done for a GNP-RL with ensemble learning and GNP-RL without ensemble learning. Out of the 16 cases analysed for the afore-mentioned benchmark, it was found out that 10 out of 16 of the tested cases, GNP-RL with ensemble learning produced better profits than GNP-RL without ensemble learning.

The ability to predict financial prices and beat the market has provided new lenses to critically look at the validity of the EMH. It is being proved that it is possible to beat the market in the mean-variance sense and predict future prices. (Cervello-Royo et al., 2015)developed stock market trading rule based on pattern recognition and technical analysis in predicting the DJIA index using intraday data over a 13.5-year period. A new version of the flag pattern was used in the price chart analysis for this study. The new rule defines when to buy or sell, the profit being pursued in each operation and the maximum bearable loss. The study is replicated in European markets using the German DAX and the British FTSE and returns provided by this new rule are higher for the European markets than in the US, thus suggesting higher inefficiency of the European Markets.

Various developments have been noted in the field of quantitative investment. In their study, (Hu et al., 2015) proposed a hybrid long-term and short-term evolutionary trend (eTrend) following algorithm that combines trend following investment strategies with the eXtended Classifier Systems (XCS) using daily trading data from 3 indices from Shanghai Stock Exchange namely: the Industrial Index, Composite Index and Business index for 12.5 years. Only 9 (2 long term and 7 short term indicators) for XCS were used in this study. The eTrend proved capable of obtaining excess return in almost all the market phases, thus eTrend naturally achieves higher end return. XCS and eTrend improve the computation effectiveness and practicability of stock trading models. Working with daily data over 6 years from 5 stock market indices namely: USA's NASDAQ; China Shanghai Composite Index; Hongkong Hang Seng Index; German DAX index and Japan Nikkei 225 Index, (Chen and Wang, 2015) developed an advanced trading system that fuses genetic network programming and mean conditional value at risk. This proposed method has a clear definition of risk and is able to construct different portfolios according to the market environment and trader's preference to risk.

A close look at the comparative experiments of Piecewise Linear Representation and Weighted Support Vector Machines (PLR-WSVM), PLR-BPN and buy and hold strategy (BHS) for 20 shares on the Shanghai Stock Exchange reveal that the PLR-SWVM outperforms all models in this experiment (Luo and Chen, 2013). As in most studies, SVM is considered for hybrid model built up because of its excellent generalization ability as well as for the fact that solutions of SVM models are globally efficient. Data scaling is done to standardize the historical data and turning points are generated using PLR. Four trading signal classifications are established for this study namely: strongly recommended buying point (SBP); strongly recommended selling point (SSP); ordinarily recommended buying point (OBP) and ordinarily recommended selling point (OSP). A set of eleven (11) technical indicators were used for the study and were standardized using the min-max Scaler. Compared to other techniques as alluded before, the PLR-WSVM outperforms its counter models registering the highest profitability and accuracy levels.

The key question is thus; can new models be developed for stock market direction prediction that can essentially increase investor profitability from their use. This essential is discussed in this research through muting of a new directional change prediction model.

Sentiment Analysis in Stock Price Prediction Initiatives

(Shynkevich et al., 2016) used multiple kernel learning models to forecast movements of 28 USA health care stock prices from the S&P 500 index over a 5-year period basing their study on different categories of news. The bag of words approach is used for feature extraction and computed chi-square values are used to select the most important features. The study found that there is a strong relationship between stock price variations and publication of important news. Group industry specific data category had an accuracy rate of 77.66% and a return of 47%.

Most studies are centred on price prediction using either fundamental or technical data, with many studies using technical indicators from historical prices. (Gunduz and Cataltepe, 2015) proposed a daily prediction model that uses financial news and price data to predict the direction of Borsa Istanbul (BIST) 100 index open prices. Given the fact that most stock price prediction experiments were done for developed countries, their study is unique in that it focuses on fusion of news and past prices for stock price prediction in an emerging financial market. Balanced Mutual Information Feature selection was chosen to pick the most relevant input data. Data for the study are over two years, 111587 news articles formed part of the data set and returns over the two years were also used as input. A Naive Bayes classifier was also used for classification in this study and its performance was measured in terms of accuracy, F-measure and macro–averaged F-measure metrics. Use of internet news only resulted in better prediction of the direction of BIST 100 with the macro –average F Measure nearly 80%. However, the overall accuracy and macro-averaged F-measures when both news sources are considered is 0.74 and 0.68 respectively.

In addition, (Li et al., 2014) study took a similar approach of combining market news and historical prices to improve prediction accuracy of future stock price return focusing on an intra-day trading context. A multi-kernel support vector regression (MKSVR) model was adopted for this study. In the pre-processing stage, absolute historical prices are translated into price indicators, thus coming up with 5 technical indicators. The chi-square feature selection technique was used for selecting the words with highest frequency. The RMSE and MAE were adopted as performance measures for this study. In addition, the study made use of price returns forecasting rather than forecasting absolute prices using stock tick prices for Hong Kong Stock Market for a year.

Taking a different approach to stock market prediction, (Bhardwaj et al., 2015) made predictions for the Indian stock markets (Sensex and Nifty) using sentiment analysis. This technique extracts subjective content by analyzing user's opinions, evaluation, sentiments, attitudes and emotions from web-based news using natural language processing and text mining tools. In this study, twitter tweets were mined for useful information for stock price prediction. Though this study makes a comparative review of similar sentiment analysis and makes use of python beautiful shop to extract features for analysis, it was silent on the results of the experiment.

The inclusion of social moods with past historical prices can better the predictive ability of forecasting models (Nguyen et al., 2015). These authors proposed a model to predict stock price movement either up or down using historical prices and information from social media only despite the fact that stock prices are affected by many micro and macro-economic factors. Daily data for 18 stocks extracted from yahoo finance website and yearly news data were used for the experiment. An SVM with a linear kernel was used for forecasting in this study. Six features namely price only, human sentiment, sentiment classification, Latent Dirichlet (LDA) based method, Joint Sentiment Topic (JST) based method and aspect-based sentiment (ABS) methods were used. Average accuracy of the model was 54.41%.

Time-series, regression and other models for stock prediction

(Wang et al., 2016) implemented an improved v-support vector regression model based on variable selection and brain storm optimization (BSO) for stock price prediction. The proposed model was compared to v-SVR-GS, v-SVR-PSO and v-SVR models and measured on three metrics namely; the MSE, MAE and the MAPE. Although the v-SVR-GS model outperforms all the other approaches, the v-SVR-BSO is considered the best since it greatly reduces computational complexity as regards calculation time during the parameter optimization process. Using 28 technical indicators as inputs into the TS Fuzzy model based on SVR's forecasting trading signals over a 2-year period on the S&P 500 index, (Chang et al., 2016) compared this proposed model to PLR-SVR, PLR-BPN and a statistical technique. The TS Fuzzy model has the highest Sharpe ratio and modified Sharpe ratio as compared to the other models. Considering further tests, the TS Fuzzy model had 22 wins compared to 17 losses in its trading strategy, thus, the model can capture 56.41% winning trade and total average profit is 18.08%.

A two-step approach was developed by (Kao et al., 2013) to predict the daily closing price for the Nikkei 225 and Shanghai Stock Exchange Composite. The first step involved use of the Nonlinear Component Analysis (NLICA) to extract independent components which were then used as input into the SVR prediction model. Daily data of futures and cash prices for four years, which were collected from the Bloomberg terminals, were used in this study and performance was measured using RMSE, MAD, MAPE, RMSPE and DS. For both indices, the proposed NLICA-SVR model outperformed its comparatives namely: LICA-SVR, PCA-SVR and SVR on all five metrics.

With use of daily closing prices extracted from NASDAQ historical quotes for Microsoft, Intel and National Bank for 4, 3 and 3 years respectively, (Kazem et al., 2013) developed a support vector regression with chaos-based firefly algorithm to predict the next day's closing prices for the three counters. The proposed SVR-CFA was compared to five models namely SVR-GA, SVR-CGA, SVR-GA, ANN and ANFIS based on two metrics of MSE and MAPE. Average errors of the proposed architecture were 0.001199 and 0.047449 for MSE and MAPE respectively and outperformed all the other models. In addition, (Lu et al., 2009) proposed a Nonlinear Independent Component Analysis - Support Vector Regression (NLICA-SVR) model to predict the Nikkei 225 closing price index. This model outperformed its alternate models namely the single SVR, the PCA-SVR and the LICA-SVR by having the smallest error rates namely: the root MSE (RMSE); mean absolute deviation (MAD); mean absolute percentage error (MAPE) and highest directional accuracy (DA). PCA was used as a feature extraction method. (Kao et al., 2013) also developed a NLICA-SVR replicative study in the Nikkei 225 and Shanghai Stock Exchange Composite (SSEC) with similar comparisons and obtaining akin results. In an endeavour to optimize the model, (Lu, 2013) advanced the NLICA-SVR model into a NLICA-SVR-PSO model which was contrasted to a LICA-SVR-PSO, KPCA-SVR-PSO, PCA-SVR-PSO, NLICA-SVR, SVR-PSO, and single SVR model in the Taiwan Stock Exchange

(TAIEX Closing Index), SSEC and Indian Stock Market (BSE) and it outperformed its alternate models.

Though single ANN architectures have been useful in stock price prediction as compared to statistical approaches, it has been noted that use of hybrid ANNs gives even much better forecasting accuracy. For instance, (Kao et al., 2013) used a hybrid approach that integrated wavelet-based feature extraction with MARS and SVR using data from the SSEC, BOVESPI, Nikkei 225 and Dow Jones Indices. In comparison to a single ARIMA, single SVR, single ANFIS, Integrated wavelet-SVR model and integrated wavelet-MARS model, the proposed hybrid model outperformed the other five models proving that hybrid models are better prediction models. Instead of working with main factor time series (MFTS) only, (Bhattacharya et al., 2016) proposed a secondary factor induced stock index time series prediction using Self Adaptive Interval Type-2 Fuzzy Sets technique, which was both trained and tested using TAIEX close price (main factor) and NASDAQ close prices (secondary factors) over a 6-year period. The T2 model offered better performance in prediction than its T1 counterpart.

It has become apparent that hybrid or fusion models are much better than single prediction model architectures. (Rather et al., 2015) proposed a novel and robust hybrid prediction model (HPM) which is created by merging predictions attained from linear models and a nonlinear model. The HPM is formed by merging results from Exponential Smoothing (ES), Autoregressive Moving Average (ARMA) and Recurrent Neural Networks (RNN) and weights for the proposed HPM were optimized through Genetic Algorithm (GA). Weekly frequency data over three years were obtained from the National Stock Exchange of India (NSE) for use in this experiment. Results from RNN outperformed all the linear models with less error and a higher correlation coefficient between the target and predicted returns. However, the HPM model outperforms the RNN. It has an MSE and MAE of 0.0009 and 0.0127 respectively. Further tests of the hybrid model were done on the Bombay Stock exchange with daily closing prices for 25 counters chosen from five sectors from 14 May 2013 to 30 December 2013. The results showed that RNN outperform all linear models and that the HPM outperforms RNN. The key question in (Rather et al., 2015) study is how different is the HPM from ensemble techniques? Is it really a novel approach or it is just an extension of ensemble techniques?

Using 2 years daily stock data for the Bombay Stock Exchange (BSE) and 4 technical indicators, (Anbalagan and Maheswari, 2015) proposed a Fuzzy Metagraph based stock market decision making, classification and prediction model for short term investors in the Indian market (BSE) with 2-year daily data. This study proposed a hybrid model that combines Fuzzy Metagraph (FM) and Fuzzy Inference System (FIS) for stock price forecasting and outperformed other models compared to it based on two error metrics namely; Root MSE (RMSE) and Mean Magnitude Relative Error (MMRE). A 98.97% accuracy level of the FM-FIS model was achieved compared to a 97.50% accuracy level f or SVM. Using the hit ratio percentage, FM out-competed random walk model, ANN, SVM with hit ratios of 75%, 50%, 69% and 73% respectively for FM, RW, ANN and SVM.

In another study by (Arafah and Muklash, 2015), fuzzy association rule on co-movement of the Jakarta Composite Index (JCI- Indonesia) stock was done for a 5-year period using daily prices. The Apriori Algorithm with fuzzy parameters was used for the study. Results reveal the minimum support parameters of 0.1, 0.07 and 0.06 as the association between the company's stock co-movement. Using data obtained on the Dow Jones Index, (Araujo, 2010)developed a Quantum-Inspired Evolutionary Hybrid Intelligent model (QIEHI) with results proving that hybrid models outperform single models. In this experiment, the QIEHI was compared to a MLP and TAEF (time delay added evolutionary forecasting) model. Pan (2010) proposed a hybrid model of PCR and GAGRNN which was compared to single PCR and single GRNN. The same observation that hybrid models are better predictors than single models was also noted in this experiment which used data from the TAIEX and China Stock Exchange. (Dash et al., 2014b) implemented a Fuzzy-Neural Network and GA hybrid model which was compared to individual neural networks models obtaining the same results that a combination of models is much better. The experiment was conducted in the Tehran Stock exchange. Similar results were noted in the Wavelet-ANFIS-QPSO-DWT model of (Bagheri et al., 2014).

As shown in the previous analysis of different prediction architecture, the key thrust was to develop a model that can extract the most useful information out of data and use it for prediction. Various feature selection and extraction techniques were made reference to. In addition, techniques varied from single to hybrid solutions and prediction movement was from traditional, statistical forecasting to machine learning techniques. The afore-mentioned researches did not consider the use of DNNs in stock price forecasting except for (Rather et al., 2015) study involving RNN. In addition, all the studies focused mostly on developing and emerging Asian markets. This current research focused on the application of new stock price prediction techniques, specifically deep neural networks, on emerging and frontier African stock markets.

Deep Learning models for stock price prediction

Stock price prediction is one of the focal areas in the artificial intelligence community. With the advent of machine learning, deep learning techniques for financial prediction are on the increase. The use of deep learning techniques has enabled investment practitioners to drift from conventional machine learning techniques to deep neural network prediction techniques for financial markets.

The LSTM has proved to being the most commonly used and most powerful tool for time series modelling in the deep learning arena (Du et al., 2019). The LSTM experiment by (Du et al., 2019) made use of Apples stock data for the period 3-11-2008 to 2-11-2018 and uses two methods to train the model. The first method is a univariate method that makes use of historical closing price as the only input variable. The second method is multi factor model which makes use of lowest price, highest price, opening price, closing price, trading volume and other factors in the historical data to predict the closing price of the next day. MSE is the loss function and MAE is used to evaluate prediction results. Results from the experiment show that the training model of the multivariate features produces better results.

In a pursuit to introduce a novel stock price prediction model, (Gao et al., 2016) implemented a deep belief network that was coupled with stock technical indicators and two dimensional principal component analysis. The authors used the S&P500 daily stock data (low, high, opening, closing prices and volume) for the period January 2004 to April 2016. Evaluation of model performance was conducted using MAE and RMSE. The results show that the prediction accuracy of the DBNs is better than the prediction accuracy of the Back propagation neural networks (BPNNs) and that the 2PCA greatly improved the performance of the system. Also focusing on the U.S.A markets, (Yu and Wu, 2019) implemented a deep learning approach for stock price prediction using a cycle embeddings with attention mechanism (CEAM) applied on dual –stage attention based RNN (DA-RNN) for stock price prediction.

Evaluations of different methods for DA-RNN with CEAM predictions were conducted for five major corporations in the US namely IBM, Yahoo (YAHOY), Intel Corporation (INTC), Apple Inc. (AAPL) and Microsoft Corporation (MSFT). The CEAM model performed best prediction in IBM, AAPL and MSFT whilst not performing well for Yahoo and Intel. However, no explanation was given to give details on why the CEAM model worked well for IBM, AAPL and MSFT whilst not performing well for Yahoo and Intel.

Using daily historical prices of the S&P 500 for 66 years from 1950 to 2016 obtained through the Yahoo finance API, (Hossain et al., 2018) developed a hybrid model (combination of LSTM and GRU) for stock price prediction. Evaluation metrics used for this experiment included MAE, MSE and MAPE. An MSE of 0.00098 and MAPE of 4.13% were achieved for this experiment. Still focusing on S&P500 index data for the period 01-01-2010 to 30-11-2017 obtained from the yahoo finance API, (Althelaya et al., 2018) implemented a bidirectional LSTM for stock prediction. MAE, RMSE and coefficient of determination were used to evaluate performance. Experimental results revealed that both BLSTM and stacked LSTM networks produced better performance for predicting short term prices as compared to long term prices. Superiority of deep learning compared to shallow neural networks as well as that BLSTM showed better performance and convergence for both short and long term predictions was noted.

(Khare et al., 2017) also implemented the LSTM for stock price prediction using minute by minute data over a one year period for the New York Stock Exchange. In addition to stock price data, three technical indicators namely trend, oscillator and momentum categories were used. The LSTM was compared to the multilayer Perceptron model which outperformed the LSTM in predicting short term prices. An LSTM deep learning model for predicting buy and sell recommendations for the Stock Exchange of Thailand (SET50) was developed and daily data for this experiment was retrieved from the yahoo finance portal for 730 days ranging from 5 January 2015 to 29 December 2017. The LSTM model was found to achieve the best accuracy in comparison to SVM, Logistic regression, random forest, Decision tree, KNN and MLP with accuracies ranging from 74.66 to 100% for the selected stocks. Also focusing on the Thailand SET50, (Jeenanunta et al., 2018) implemented an LSTM to predict five companies in the SET50 index in comparison to a deep belief network. The five companies were selected to represent how the model deals with stocks with different volatilities. However, the paper is silent on how the volatility is measured. Input parameters included open, high, low, close prices, volume, 3 day simple and moving average. Key results from this experiment point to the fact that LSTM is suitable for low volatility stocks whilst deep belief networks are suitable for high volatility stocks. An important consideration is the assessment of the usefulness of the LSTM and other deep neural networks in African stock markets which are believed to be very volatile.

In an endeavour to extract features and get a summary representation of the daily market, (Zeng and Liu, 2018) implemented a stock price fluctuating forecast model based on the LSTM and compared it to a neural network regards data fitting degree, prediction accuracy and prediction bias. The SSE50 Index (Shanghai stock exchange) was considered for this study. Key findings from this study are that the weekly line prediction model is more meaningful than the daily line or monthly line. (Chen and Daves, 2018) developed a stock market embedding and prediction LSTM deep learning model for Chinese A-share stock HS300 index for the period 2004-2018.Results from this experiment show that LSTM based on attention mechanism with market vector input is the most effective method. The attention mechanism reduced MSE value by 55.68% on average and use of market vector reduced MSE by 92.42% in comparison to 14 widely used technical indicators. This shows a growing use of attention mechanisms to stock price prediction.

(Cheng et al., 2018) used an applied attention based LSTM neural network in stock prediction for the Taiwan stock exchange. This technique was tied to stock trading strategy and its results were calculated based on the return. Though the paper made use of accuracy, precision, recall and f-measure as network performance evaluation metrics, the paper is devoid of results. Hence, this makes it difficult to compare the experiment results to other similar simulations. (Chen et al., 2016) proposed a deep convolutional neural network for financial time series data using approximately 1 054 959 historical intraday one minute data of the Taiwan stock index futures covering the period 2 January 2001 to 24 April 2015. Good classification of future trends was achieved for the transformed Taiwan dataset which was turned into a two dimensional image data as input for the proposed CNN. It was proven that the CNN could extract useful features and was able to recognise the behaviours of the financial markets based upon the proposed two dimensional time series data representation methods. Combining the CRNN and LSTM structure, (Gao et al., 2018) were able to predict the Taiwan stock exchange with reasonable accuracy. The proposed method called convolutionalLSTM, in which the first layer is the CNN which feeds into two layers of LSTM before output is produced. The ConvolutionalLSTM was compared to a LSTM model. Though the results of the LSTM are better than the ConvLSTM model, it was found out that the ConvLSTM had more neural network stability.

Unlike (Chen et al., 2016), a one dimensional CNN to predict financial market movement was introduced by (Wang et al., 2018). In a pursuit to avoid use of traditional technical indicators and avoid biases caused by the selection of these indicators, the authors resorted to use of CNN without incorporation of technical indicators. Four commodity futures and two equity index futures for the period January 2010 to October 2017 were considered. Each record was comprised of 5 minute trading records which included the following attributes namely open price, high price, low price, close price and trading volume. SVMs and Deep Feed-forward Networks were used as baselines for comparisons. The proposed method outperformed the baselines by 12.4%-63.3% on average return and 99-245% on Sharpe ratio over previous machine learning approaches. Interestingly, new proposed methods now take a paradigm shift from using accuracy metrics to use of financial metrics such as the Sharpe ratio. It may be necessary in future to evaluate algorithm performance based on more investment related metrics.

It is worth noting that the LSTM is amongst the mostly used deep learning models. (Qian and Chen, 2019) also implemented an LSTM model to predict stock prices. They made use of three stocks with similar trends and different stability. However this paper did not explain where the three stocks were obtained from. This makes verifiability of the experiments a challenge. Nevertheless, the authors found out that the error rate of the LSTM was 66.78% lower than that of ARIMA. Hence, the LSTM performs better than ARIMA. Focusing on the Athens SE FTSE/ASE large cap index, (Mourelatos et al., 2018) used an LSTM for financial indices modelling and trading utilizing. The LSTM was compared to a hybrid approach that combined genetic algorithms and SVMs. Adoption of financial metrics is becoming a norm with the following metrics considered for this (Mourelatos et al., 2018) study; annualised return, annualised return with transaction costs, annualised volatility, sharpe ratio, Sharpe ratio with transaction costs, positions taken and correct directional change. The GA-SVR and LSTM showed similar behaviour with significant differences in the financial metrics been noticeable. The LSTM was able to generate more financial gains in most scenarios.

In another study, (Sreelekshmy et al., 2017) ran a stock price prediction experiment that compared LSTM, RNN and a CNN sliding window model. Minute wise data for 1721 NSE listed companies for the period of July 2014 to June 2015 was used. The CNN model outperformed the other two models. This is owing to the fact that CNN does not depend on any previous information for prediction and uses the current window for prediction. This enables the model to understand the dynamical changes and patterns occurring in the current window. LSTM and RNN make use of information from past lags to predict the future instances. Since the stock market is a highly dynamical system, there is bound to be changes in the patterns and dynamics existing in the system making the RNN and LSTM models fail to capture the dynamical changes accurately. In addition the deep learning models also outperformed ARIMA. As an attempt to better prediction performance, hybridization of CNN to deep neural networks may be ideal.

In an endeavour to extend on the DNN, (Zhang et al., 2018)proposed a deep and wide neural network (DWNN) in which a CNN layer is added to the RNNs hidden transfer process. Daily data from China's SSE sandstorm sector was used in training the model and consisted of open, high, low, close prices and volume figures. The results point to the fact that DWNN model was able to reduce the prediction MSE by 30% compared to the general RNN model. Taking a different approach, Wang (2019) introduced a deep convolutional fuzzy system (DCFS) for stock index prediction of the Hang Seng index of the Hong Kong stock market. It was noted that the proposed method had the following advantages. It was fast, highly interpretable, flexible, mistakes could be corrected easily, and it can be implemented on simple devices, supports on-line learning and is suitable for high dimensional problems. With a focus on the Russell 100 index, (Choi and Renelle, 2019) implemented a deep learning model to forecast price momentum in 850-950 US listed stocks per year for the 22 year period from 1996-2017. The entire period consisted of 180 rolling monthly forecast origins. The deep learning price momentum (DLPM) model outperforms the returns of the conventional price momentum (MOM). Thus the robustness of the DPLM momentum factor is evident in both the returns and the performance/volatility dimension.

Stock price prediction exercises are varied with some focusing on predicting the next day's closing price or stock market direction. (Zarkias et al., 2019) developed a deep reinforcement learning model for financial trading using a price trailing approach. The model was developed to follow the trend of the price and gets rewarded if it behaves optimally. Though this approach was used for exchange rate determination, it can be extended to stock price forecasting. A model that can combine stock trend prediction and stock price prediction is a must if investors are to optimally profiteer from use of trading algorithms, a gap that this research focused on.

Increased use of deep learning techniques for stock market analysis and prediction is now noticeable. In an experiment by (Chong et al., 2017), a model was constructed using stock returns from the KOPSI market in South Korea. The sample consisted of the top 38 stocks according to market capitalisation. The data set is split 80/20 for training and test set. This has become a commonly accepted ratio for training and test splits. In addition, the 20% test is also split into a validation and test set. The test was designed to assess the up or down movement of future returns and was assessed on normalised mean square error (NMSE), root mean square error (RMSE), mean absolute error (MAE) and Mutual Information(MI). The deep neural networks performed better when compared to a linear autoregressive model in the training set. However, this advantage mostly disappears in the test set. The authors of the paper proclaim their study to be one of the most comprehensive studies but this is disputed when compared to this current study which compares seven different algorithms (RNN, LSTM, GRU, BRNN, BLSTM, BGRU, GAM) in stock market analysis and prediction.

It has also being noted that DNNs such as LSTM are known to outperform statistical time series due to their mechanism of learning to vectorize historical information (Le and Xie, 2018). Extending on this foundation, (Le and Xie, 2018) proposed a new deep architecture called a recurrent embedding kernel that has an ability to learn to make optimal decisions by making reference to the entire history rather than just the memory vectors. This proposed model was compared to RNN, LSTM and GRU using daily data of six ETFS (SPY, DIA, IYR, GLD, VDE and GDX) to predict daily price prediction. Results show that REK consistently outperforms the other models by attaining accuracies over 70% but less than 72%. All the other models results were in 60-70% range.

In another experiment, (Shah et al., 2018) undertook a comparative study of LSTM and DNN for stock price prediction. LSTM- RNN and DNN were compared to predict the daily and weekly movements in the Indian BSE Sensex Index measured on RMSE and directional accuracy. Unlike most experiments, this work used a 90/10 split between training and test set and dropout was not applied. The LSTM - RNN model did a better job in predicting weekly movements than the DNN as it was able to identify the directionality of the changes in the true data.

(Tang et al., 2018) proposed an algorithm of turning point prediction named piecewise linear representation improved random forest (PLR-IRF) for macro trend analysis. In accordance to the deep learning theory, the authors adopt a deep recursive neural network (DRNN) to design the investment decision model. The authors made use of data from 20 stocks of the Shanghai stock exchange for the period 4 January 2010 to 6 January 2012. This data comprised of transaction data and indicator data. On the side of transaction data, opening price, highest price, lowest price, closing price, volume and turnover were considered. Indicator data included 14 absolute indicators and 15 relative indicators. It was noted that the critical error rate of the indicators based on the PLR-IRF was zero implying no misjudgement of trend prediction either as a strong buy or sell turning point. The investment model used DRNN to recursively generate trading strategy. Since the DRNN has an ability to dynamically formulate investment strategies, it provided more valuable reference to stock market investors.

In another experiment, (Unadkat et al., 2018) implemented a RNN and LSTM to the prediction of Google Inc, Adobe Systems Inc, TESLA Inc and Facebook Inc with their data derived from the Quandl website. The data was collected for different periods, which could comprise the comparative approach taken for the various stocks. Training was done for RNN-LSTM model with timestamps for 20 days and 60 days. It was found out that 20 day timestamps achieved better results for all stocks. Hence, a conclusion to the effect that fluctuation that happen within a recent past have more effect on the opening price than fluctuations which occurred a long time back. In other words, the authors found out that the most recent patterns have a great impact on the future price of a stock than the variations that happened a long time back.

Working with dataset for INFOSYS Ltd and NSE NIFTY50 Index for the period 11 December 2007 to 11 December 2017, (Sachdeva et al., 2019) developed an effective time series analysis model for equity market prediction using a RNN deep learning technique. Price information included open, high, low and closing prices. The best accuracy obtained was 97.64% when 60 time steps and RMSprop was used as an optimiser.

Though use of deep neural networks has been introduced to the financial domain mostly in developed stock markets and in developing Asian stock markets, the LSTM has proved to be the widely used architecture. The testing of other deep neural networks in the financial domain remains scanty and needs to be closely looked at. In addition, all other deep neural network architectures have not been adequately tested for emerging and frontier African stock markets, a key gap this current research works on and work on increasing their prediction accuracy. In addition, most deep neural architectures that have been implemented include RNN, LSTM, CNN and GRU, which are unidirectional in nature. An analysis on whether bidirectional deep neural architectures can improve prediction accuracy is a gap that this research is centred on.

3.6 Conceptual Frameworks

This research was premised on the APT in that the following K factors (inflation, interest rates, money supply and exchange rates) are believed to affect stock index movement. A movement in each variable either positively or negatively has an impact on the final stock index prices. The research takes three approaches to stock index prediction. The first approach made application of deep neural networks to stock index prediction using historical prices in the form of open, high, low, close and volume (OHLCV) to predict the next day's closing price. This application was premised on the following theories; EMH, CAS, AMH and APT. Second was the application of the k factors to stock price movement using a time series data approach. This incorporated four macroeconomic variables (money supply, inflation, exchange rate and interest rate) to ascertain their impact on stock markets closing price. Lastly, the research developed a statistical prediction approach to predict the next day's closing price. Figure 3.1 and 3.2 below present the conceptual frameworks for this research.

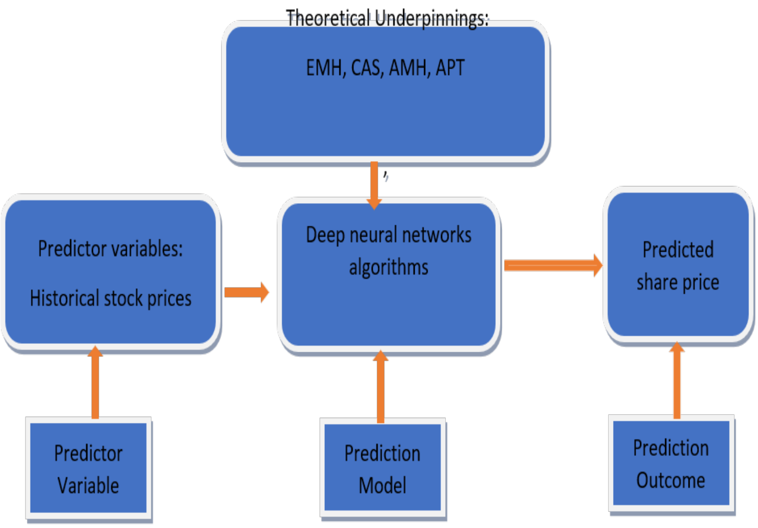

FIGURE 3.1: Conceptual Framework 1

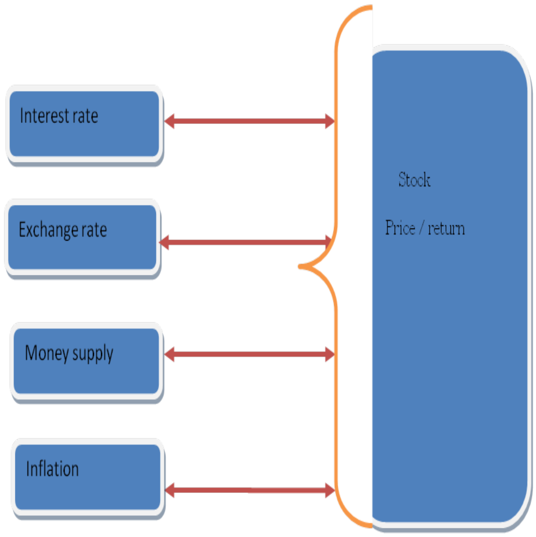

FIGURE 3.2: Conceptual Framework 2

3.7 Chapter Summary

This chapter looked at the various stock market prediction initiatives that have been undertaken in financial time series predictions. The motives and challenges in financial time series prediction were discussed. An outline of the various prediction models was also given, demonstrating the evolution of ANNs to DNNs. Some of the ANNs mentioned had different layers, with some been two, three and four layered feed-forward ANNs which produced different prediction results. Notably, few ANNs encompassed bidirectionality aspects. Also, lack of empirical evidence in the use of generalised additive models for stock price prediction was also noted. The key factors that move stock prices were also discussed. The next chapter will discuss the different stock price predictions adopted for this research.

Chapter 4

Stock Price Prediction Models

4.1 Introduction

This chapter looks at the various prediction techniques used in stock price prediction initiatives in an endeavor to develop models for stock price prediction. Section 4.2 reviews statistical approaches to stock price prediction while section 4.3 discusses artificial neural networks. Sections 4.4 and 4.5 expound on the various machine learning techniques in stock price prediction with a focus on deep learning architectures used for time series prediction which can be adopted for stock price prediction. Despite the availability of various prediction models in time series analysis, this research settled for a GAM statistical approach and the following deep neural networks, RNN, LSTM, GRU, BRNN, BLSTM and BGRU. A discussion of the performance metrics adopted for this study is in sections 4.6 and the chapter summary follows up.

4.2 Statistical Approaches to Stock Price Prediction

Efforts to come up with prediction models have been ongoing with movements from statistical approaches such as Autoregressive Integrated Moving Averages (ARIMA) model to nonlinear statistical approaches such as Bilenar models, Threshold Autoregressive models, General State Dependent models and Generalised Additive Models (GAMs). For the purpose of this research, GAM modelling was adopted with an intention to cross validate the notion that ANNs outperform statistical approaches in time series prediction (Abdelmouez et al., 2007; Egeli et al., 2003; Altay and Satman, 2005; Avci, 2007; Kumar and Thenmozhi, 2009; Senol and Ozturan, 2008).

A general consensus amongst academic researchers is that GAMs are widely used in data analysis to explore the nonlinear effects of the covariates on the response variable. They are not only reasonably flexible for prediction but also have the advantage of avoiding the "curse of dimensionality." GAM is a statistical approach for nonparametric or semi parametric modelling and it has demonstrated its ability to capture nonlinear relationships between explanatory variables and response variables (Hastie and Tibshirani, 1986). It is for this reason that this model is compared to neural networks to determine if it could predict data nonlinearity with much success. The GAM model adopted for this research is a sum game of smooth functions as shown in the following formula:

$$g(E(y_i) = \beta_0 + f1(x_1) + ... + fp(x_p) + \epsilon_i$$

where y_i is some exponential family distribution, and i=1,...,N; g is a link function (identical, logarithmic or inverse); y is a response variable; $x_1,\ldots,x_p$ are independent variables; β_0 is an intercept; $f_1,\ldots,f_p$ are unknown smooth functions and i is an i.i.d. random error. Therefore, the model can be written in a linear way like this:

$$g(E(y)) = \beta_x + \epsilon_i$$

4.3 Artificial Neural Networks

With an inspiration from the brain system, ANNs as mathematical or computational modelling techniques impersonate the human brain and nervous system and the human's brain capability to classify patterns or to make predictions or decisions based on past experience (Peace et al., 2015).ANNs are self adaptive and data driven non-linear models simulating the human nervous systems having the task of self-organizing, self-study and associated memory and are characterized by parallelism, nonlinearity, high robustness, generalization capability and learning (Trifan, 2010). ANNs learn from patterns by capturing hidden functional relationships among the data and have proven to be universal approximators with the ability to fit any underlying data generating process.

The justified increased use of ANNs is a result of their nonlinear approximation ability and characteristic of self-learning, self-adaption and the advantage of automatically extracting knowledge of economic activities from historical data (Shan et al., 2015). In addition, ANNs are also more ideal for complex systems exhibiting nonlinearity and where there is sufficient data or observation to mine the information (Muhammad and Saeed, 2011). Owing to their predictive ability, robust behavioural characteristics in uncertain environments and adaptability to different fields, neural networks are assumed to have immense potential in the financial time series prediction field (Reid et al., 2014).

4.4 Deep Learning Models

4.4.1 Motivation for use of Deep Learning Architectures

The key motivation for the use of deep neural networks which are known to be powerful ANNs (Dixon et al., 2015) in this study was their ability to identify hidden patterns and underlying dynamics in the data through a self learning process (Sreelekshmy et al., 2017). Stock market data are characterised by nonlinearity and dynamism, hence a need for such deep algorithms to establish hidden patterns and dynamics. Sections 4.4.2 - 4.5.3 that follow explain the deep learning architectures adopted for this research.

4.4.2 Recurrent Neural Networks

Application of RNNs for time series prediction cuts across disciplinary domains such as finance in stock price prediction (Rather et al., 2015; Lin et al., 2009); language modelling for automatic speech recognition (ASR) as exhibited in the works of (Mikolov et al., 2010), robotic tasks (Kim, 1998) and handwriting recognition (Graves et al., 2009).

The RNNs are a class of artificial neural networks whose connections between units form cycles which have the ability to make use of sequential information performing the same task for every element in a sequence (Kadari et al., 2018). Unlike in forward networks, RNNs make use of feedback connections in pursuit of modeling spatial and temporal dependencies between input and output series in order to make the initial and past states of the neurons involved in a series of processing.

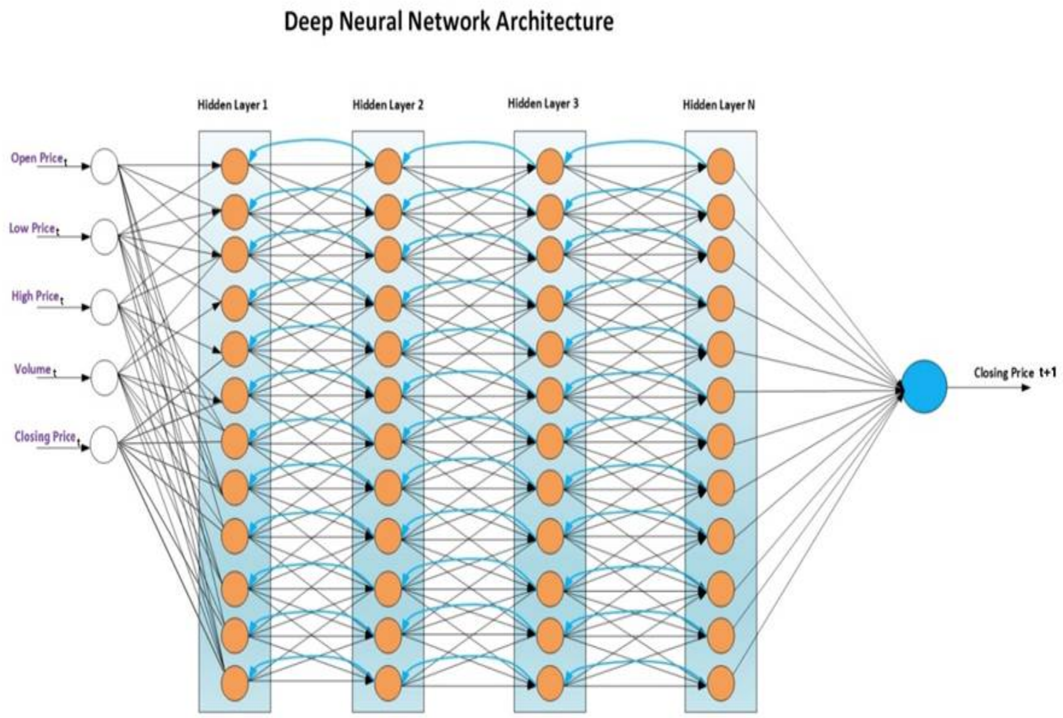

FIGURE 4.1: Recurrent Neural Networks

In other words, there are two inputs in an RNN, the current input and the past input. A combination of these inputs make predictions more accurate (Unadkat et al., 2018; Mourelatos et al., 2018). RNNs have internal memory that can store data and relate it to the current data. Therefore, sequential data can be easily compared in context with the past data, hence producing far better results than other memory less algorithms (Unadkat et al., 2018). RNNs have the benefit of their "memory feature" which can be used to extract time dependencies in the data (Lawrence, 1997). If a RNN has a layer and sufficient number of hidden units, it can approximate any measurable sequence-to-sequence mapping to an arbitrary precision, hence making them ideal for stock forecasting (Zhuge et al., 2017). The output of RNNs at time t depends not only on the current input and the weight, but also on previous inputs as shown below;

$$U_t = g(W \bullet X_t + R \bullet U_{t-1} + b)$$

Where X_t is the input at time point t; W and R are weight matrices of the network; b is the bias vector of the network; and $\bullet isaselectedactivationfunction.$

One key limitation of RNN is that it has a limited internal memory, so it stores values from the recent past and not from the beginning. In addition, RNNs also suffer from the vanishing gradient problem and/or exploding gradient problem. This is whereby the gradient of some of the weights begin to develop either into too small or too large values upon the network being folded for too many time steps (Gamboa; Zhuge et al., 2017). This problem leads to exponentially small gradients and a decay of information through time. The gradient is a measure of change in the weights in a neural network in response to the error rate calculated. When the gradient becomes so small or closer to zero, the model will not learn anything new or it learns at such a smaller rate and this is called the vanishing gradient problem. If the weight assigned to a particular layer is extremely large, it is called the exploding gradient problem and it can be controlled by use of thresholds (Unadkat et al., 2018).

4.4.3 LSTM

In pursuit of overcoming the shortcomings of recurrent neural networks (RNNs), the Long Term Short Memory (LSTM), which is an extension of RNNs, can learn long term dependency information (Zhang et al., 2017a; Kadari et al., 2018) thereby capturing both short and long term memories(Le and Xie, 2018) unlike RNs that capture short term memory only. LSTMs are able to solve the vanishing gradient problem in RNNs.

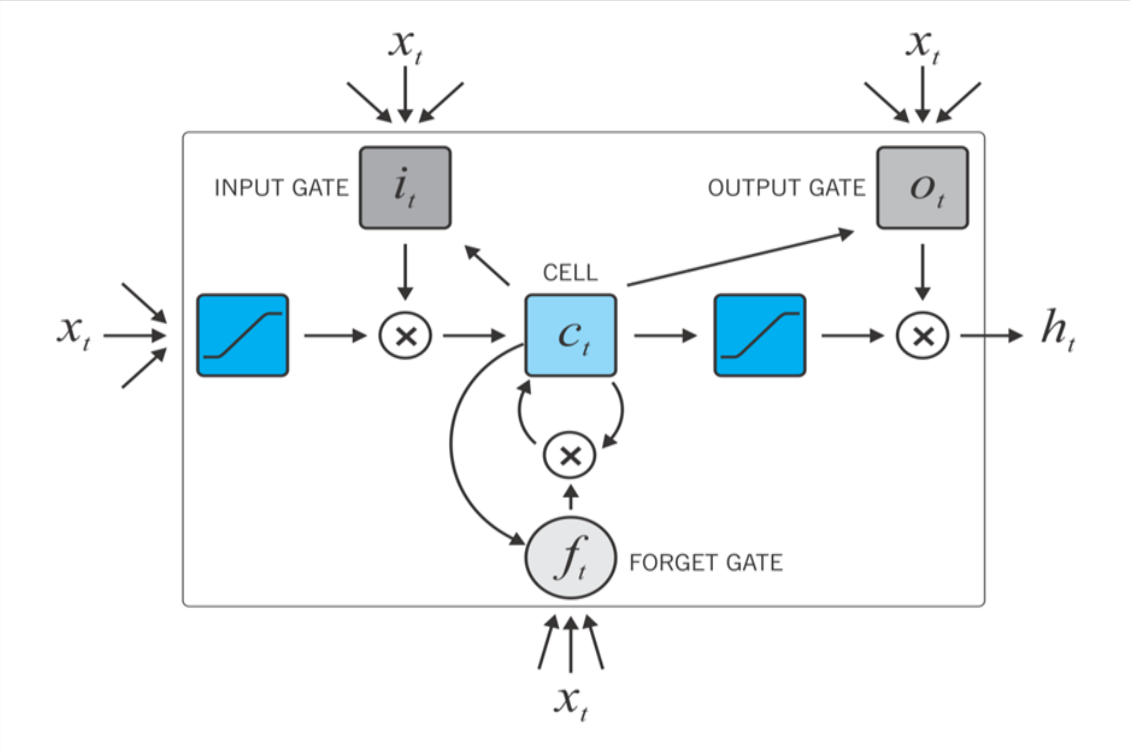

FIGURE 4.2: LSTM

As explicitly shown in figure 4.2, the LSTM architecture comprises a number of processing steps with three main gates namely the input gate, forget gate and output gate in addition to a cell state. Gates are applied at each activation unit to preserve long range memory across the input sequence (Dindi et al., 2012). In other words, the chief inspiration to introducing memory blocks is to decide the degree to which LSTM units keep the previous state and memorize the extracted features of the current data input. The LSTM therefore addresses the problem of limited memory information through the gating system by replacing hidden layers with memory blocks which are then controlled and updated by the gates allowing the network to remember information over long periods of time (Kadari et al., 2018).

The LSTM defines gated cells that can act on the received input by either blocking or passing information based on the importance of the data element (Althelaya et al., 2018). The three adaptive and multiplicative gates (input, forget, ouput) in the memory block perform different functions. The cell state connection stores the required memory information, while its internal entry control structure updates and outputs the control information. The forget gate determines the information content to be discarded by the model from the cell state by reading the previous time output information $h_{t-1} and$the current input information X$_t$,outputting a value between 0 and 1,and multiplying each cell state c$_{t-1}$. A value of 1 implies a complete retention of the previous information and 0 implies a complete discard of the previous information (Du et al., 2019). In the formula below, the forget output is $(f_t), W_f and b_f$are the weights and offset matrices of the neural network layer, respectively.

$$f_t = (Wf \bullet [h_{t-1}, x_t] + b_f)$$

The input gate functionality is in two parts; one part is for partial discarding of old information and the other part is the partial reservation of the new information. Results from these two functions are summed together to complete the update of the cell state. Calculations in the input gate are as follows;

$$i_t = (Wi \bullet [h_{t-1}, x_t] + b_i)$$
$$C\tilde{}_t = tanh(W_c \bullet [h_{t-1}, x_t] + b_c$$
$$C_t = f_t * C_{t-1} + i_t * C\tilde{}_t$$

where C~t is a new state value vector created by the tanh network layer in preparation for cell state update in (7).

The output layer is responsible for determining the output of the message and the internal sigmoid layer determines which portion of the information shall be output. To obtain final output, the cell state is processed by the tanh excitation function which is multiplied by the output of the sigmoid gate as shown in equations (8) and (9) below.

$$o_t = (W_o \bullet [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * tanh(C_t)$$

where $(\bullet)$ is the sigmoid function[1], $tanh(\bullet)$[2] is the hyperbolic tangent, x_t is the input vector, h_t is the output vector, C_t is a cell state vector. W are weights as before and b are biases. F_t, i_t and o_t are the forget, input and output gates of the block.A key consideration is that * is not a matrix multiplication but a Schur product i.e. entry wise product. It is on this premise that LSTMs in this research were considered to cater the RNN shortfalls. Unlike the RNN, LSTMs have the advantage of capturing autoregressive structures of arbitrary lengths and require no prior specification of how many 'feedback loops' to incorporate (Hansson, 2017). The LSTM structure through its various gates and cell system will be able to screen relevant factors necessary for determining the most suitable next price, hence improving on this computationally aided investment decision making process.

4.4.4 GRU

A Gated Recurrent Unit was structured to make each recurrent unit adaptively capture dependencies of different time scales. The GRU just like the LSTM has gating units which modulate information flow inside the unit without containing separate memory cells (Chung et al., 2014). These gates for the GRU are the reset and update gates as shown in Figure 4.3.

Unlike the LSTM, the GRU has the potential to analyze feedback sequences on multiple scales and avoids the gradient vanishing problem during training. Therefore, the model can learn both short and long-term dependencies . Also noting the

[1]Sigmoid(x) = 1/(1+exp(-x))
[2]Tanh(x) = (ex - e-x)/(ex + e-x)

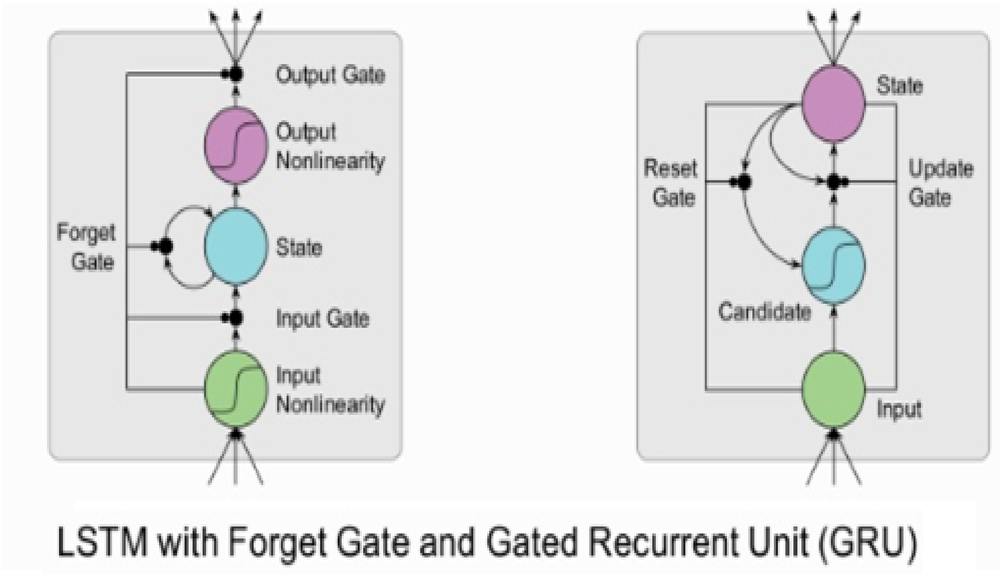

FIGURE 4.3: GRU

same advantages are (Siah and Myers, 2016) who postulate that using GRUs is advantageous in that they avoid the gradient diminishing problem through the rest gate and update gates. The purpose of the reset gate is to determine how to combine new input with the previous hidden state whilst the update gate determines how much of the previous hidden state should be retained in the current hidden state.

The GRU improvement from the LSTM is that it combines the forget and input gates into a single update gate and also merging the cell state and the hidden states (Huynh et al., 2017). The overall GRU architecture is much simpler as compared to the LSTM but is often faster. The GRU is defined by the following equations:

$$\begin{aligned} z_t &= (W_z \bullet [h_{t-1}, x_t]) \\ r_t &= (W_r \bullet [h_{t-1}, x_t]) \\ h\tilde{} &= tanh(W \bullet [r_t * h_{t-1}, x_t]) \\ h_t &= (1 - z_t) * h_{t-1} + z_t * h\tilde{}_t \end{aligned}$$

Where z_t and r_t are the value of the update gate and reset gate respectively. Z_t is used to control on what extent current state ht should keep from previous state h_{t-1}. The more significant value of the update gate, the more information of the previous state is brought into the computation. The reset gate r_t is used to control the degree of ignoring the status information at the previous moment and the smaller the reset gate value is, the more it would ignore its previous state.

4.5 Bidirectional Prediction Architectures

4.5.1 Bidirectional RNN

Simple RNNs contain the entire sentence performing processing of sentence with the output depending on the previous computations. BRNNs perform computations in both left and right directions (Kadari et al., 2018). Therefore, BRNNs are trained to predict both in the positive and negative time directions simultaneously as shown in Figure 4.4. Hence, conceptually, the BRNN can consider the context of the input feature vectors across all the preceding and succeeding time steps to predict the output label of the current time (Atsunori and Hori, 2017).

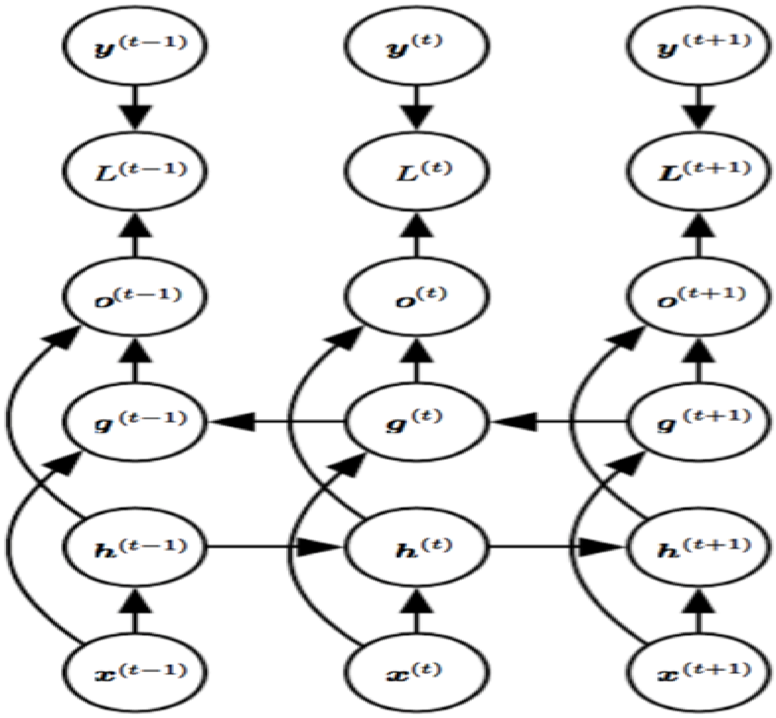

FIGURE 4.4: Bidirectional RNN Architecture

Since bidirectional architectures have been proposed to capture both past and future information, they have achieved higher prediction accuracy. Output from both sequences i.e. the forward hidden layer and backward hidden layer is concatenated to provide final output at Y_t. In this architecture, the forward and backward activation vectors are recursively propagated through its forward and backward hidden layers that each have a self-loop connection.

BRNNs process data in both directions using two separate hidden layers, namely the forward and backward hidden layers. These two layers are feed forwards to the same output layer. Computationally, the BRNN is computed using the following; the forward hidden sequence $\overrightarrow{h}$, the backward hidden sequence $\overleftarrow{h}$ and the output sequence y by iterating the backward layer from t = T to 1, the forward layer from t =1 to T and then updating the output layer. The computation display of the BRNN is as follows;

$$\overrightarrow{r_t} = sigm(\overrightarrow{W_x r} X_t + \overrightarrow{W_h r} \overrightarrow{h_{t-1}} + \overrightarrow{b_r})$$

$$
\begin{aligned}
z_t &= sigm(\overleftarrow{W_{xz}} X_t + \overleftarrow{W_{hz}} \overleftarrow{h_{t-1}} + \overleftarrow{b_z}) \\
h\tilde{}_t &= tanh(\overleftarrow{W_{xh}} X_t + \overrightarrow{W_h h}(\overrightarrow{r_t} \bullet \overleftarrow{h_{t-1}}) + \overleftarrow{b_h} \\
\overrightarrow{h_t} &= \overrightarrow{z_t} \bullet \overleftarrow{h_{t-1}} + (1 - \overrightarrow{z_{t-1}} \bullet (h\tilde{}_t)
\end{aligned}
$$

4.5.2 Bidirectional LSTM and BGRU

Bidirectional Long Short-Term Memory models (BLSTM) shown in Figure 4.5 are basically an extension of the unidirectional LSTM networks by introducing two separate layers: one processes the sequence from left to right, the other from right to left, then the two outputs from each sequence are then concatenated to form the final output (Kadari et al., 2018). The same applies for BGRUs which are an extension of GRUs as shown in Figure 4.6. All the bidirectional architectures rely not only on past information as input but also tap from future states. Bidirectional architectures input data is not fixed and can also reach into future states for input, hence making the output layer get information from both the past and the future (Persio and Honchar, 2017)

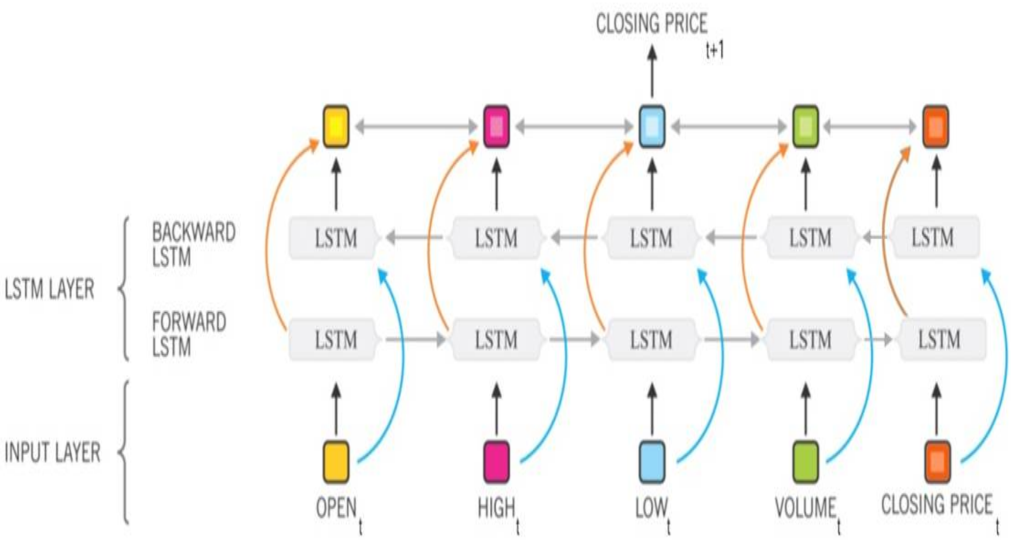

FIGURE 4.5: BLSTM Architecture

4.6 Evaluation Metrics

The loss function is a metric of how distant away a particular situation is from its optimal solution to the problem being solved (Hoang, 2017). In this research, more reliable metrics such as root mean square error (RMSE) and mean absolute percentage error (MAPE) are used to evaluate performance of the model (Wielgosz et al., 2017). In addition to these important evaluation metrics, this study also adopted

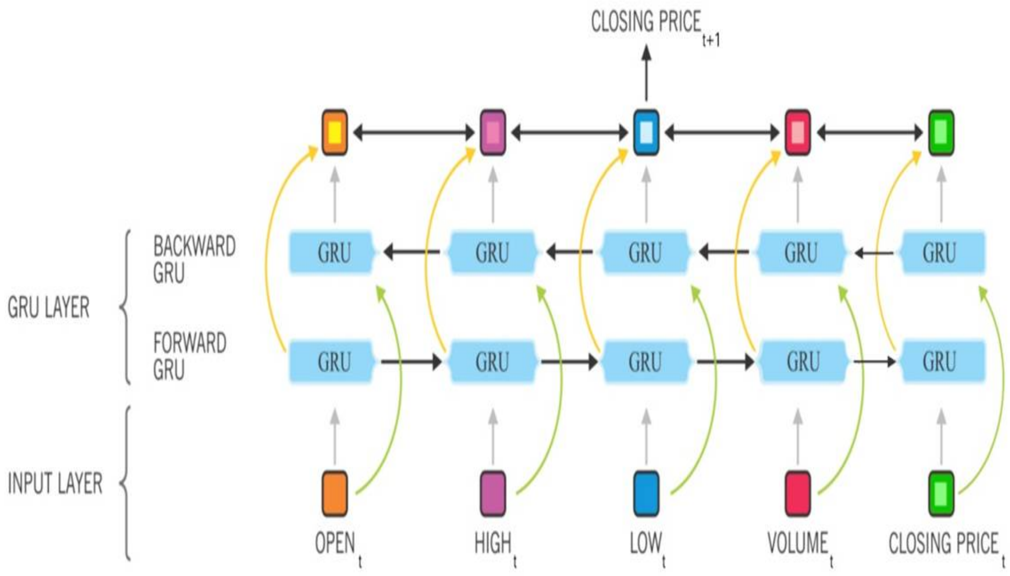

FIGURE 4.6: Bidirectional GRU Architecture

mean absolute deviation (MAD), mean square error (MSE) and Accuracy as additional metrics to have a robust check on algorithm performance. The formulas of the aforementioned evaluation measures are outlined in Eqs. (18) - (22).

$$MAD = \frac{\sum_{t=1}^{n} |At - Ft|)}{n}$$

$$MSE = \frac{\sum_{t=1}^{n} (At - Ft)^2)}{n}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (At - Ft)^2)}{n}}$$

$$MAPE = \frac{\sum_{t=1}^{n} |At - Ft|)/At)}{n} * 100$$

$$Accuracy = \frac{\sum_{t=1}^{n} Predictionsi)}{n}$$

The MAD is the mean distance between each data point and mean.It gives an idea about the variability in a dataset and helps in getting a sense of how "spread out" the values in a data set are. The MSE is a measure of the quality of the estimator and it is always non-negative with values closer to zero indicating better prediction accuracy.It measures the average of the squares of the errors,that is, the average squared difference between the estimated values and the actual value. MSE is a risk function, corresponding to the expected value of the squared error loss. RMSE is the square root of the average of squared errors representing the standard deviation of differences between observed values and predicted values of a sample. Thus RMSE is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are and thus, RMSE is a measure of how spread out these residuals are. In other words, it points on how concentrated the data is around the line of best fit. MAPE is measured in percentage terms and used as a loss function in regression problems for machine learning.MAPE is the mean or average of the absolute percentage errors of forecasts where error is defined as actual or observed value minus the forecasted value. This measure is easy to understand because it provides the error in terms of percentages. . The smaller the values of MAD, MSE, RMSE and MAPE, the closer are the predicted values to the actual values. Accuracy reflects the percentage level at which the algorithms were able to accurately predict the next day's closing price for the selected dataset's. A high prediction accuracy is most desirable and indicates an increased prediction performance of the model(s). For MAD,MSE,RMSE and MAPE, At and Ft represent the actual and forecast values whilst n is the number of sample points used.

4.7 Chapter Summary

The motivation for use of deep neural nets is to achieve increased prediction performance. This research firstly compares the GAM statistical approach to neural network models. As GAM is one of the recent statistical models which can also map nonlinear sequences, it was the research's intention to find out how well it predicts in comparison to ANNs, in this case DNNs. In addition, deeper neural networks (BRNN, BLSTM and BGRU) are believed to be better predictors than simple deep networks such as RNN, LSTM and GRU owing to the bidirectionality aspects of their architectures. The research aimed at showing this progression in terms of prediction accuracy, hence the need to review and test the six DNN architectures.

Simple RNNs suffer from the curse of dimensionality. They are faced with vanishing gradient challenge and only work with recent temporal data. LSTMs resolve this by establishing long term memory into their architecture. GRUs merged the gates to come up with only two gates, that is the reset and update gate, hence improving speed of learning. This research settled for RNN, LSTM, GRU, BRNN, BLSTM, BGRU and GAM to predict the selected African emerging and frontier stock markets. Through this, the usefulness of the aforementioned architectures is examined for financial time series forecasting for the selected African emerging and frontier stock markets. The chapter that follows will look at the methodology adopted for the architectures in detail.

Chapter 5

Research Methodology

5.1 Introduction

This chapter looks at the prediction models implemented for this research in detail. Based on insight from literature review in chapters 3 and 4, a machine learning model and a statistical model for prediction are explained in this chapter. An outline of the prediction framework explaining the sequence of steps involved in the machine learning pipeline is laid out in section 5.2. Matters regarding data sources and data collection are also expounded in section 5.3 while section 5.4 focuses on model selection and explains how the data is prepared for data analysis. In section 5.5, training results are reported whilst in section 5.6 the researcher looks into the time series multivariate econometric prediction model. The chapter concludes with a summary section.

5.2 Prediction Framework using Machine Learning Techniques

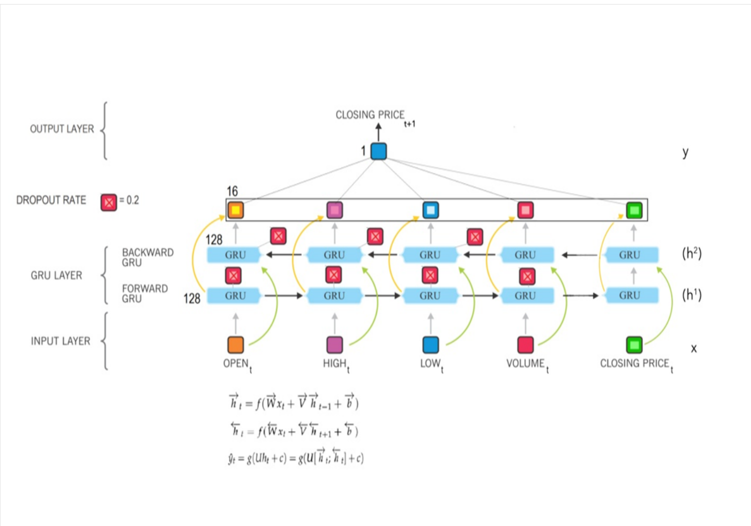

FIGURE 5.1: Prediction Framework

Figure 1 provides a depiction of the architecture model created for stock price prediction initiatives for this research.The prediction framework adopted for this research is a composition of pre-processing, learning, evaluation and prediction stages. Each stage of the framework encompasses various sub-steps which are explained in greater detail in the subsequent sections.

5.3 Data and Data Sources

For the purposes of this research, daily stock index data and macroeconomic data were considered for ten African countries[1] based on market capitalization. In addition, prediction in these African countries was benchmarked to a developed financial market, the S&P 500 (USA). The S&P 500 is believed to be representative of the United States top 500 firms. The S&P 500 predictions are compared to the ten African countries which comprise emerging and frontier stock markets. The Bloomberg database was used to collect the daily stock index data in the form of open, high, low and closing price which was used to predict the index next time step closing stock prices. The Bloomberg symbols used to obtain the historical prices were PX_Open, PX_High, PX_Low and PX_Last for open, high, low and closing prices. The closing price was chosen to be the predictor variable because it reflects all the activities of the index in a trading day. The start and end periods of experiments for the bourses are the same so as to ensure a comparable analysis for the stock markets.

The period 2012 to 2017 was considered for the prediction task in order to generate a large sample of recent data points and also include periods of great influence to the stock markets such as the China stock market crash and various political and policy system changes. Key global economic events such as the China crash of 2016, installation of Donald Trump as the new President of the United States in November 2016 sent global shock waves across the globe. China and the USA are amongst the major trading partners for most African countries included in this research. African markets are cointegrated to the USA and China markets. Owing to systemic risk as a result of cointegration, a major shock in these markets is transmitted to the African trading partner's economies. Second, a lot of key political, economic and policy shifts happened during this period in Africa. As a result, stock markets could not be spared from such economic shocks.

In addition to the above, the selected African markets in this study are volatile as shown in Figure 5.2 below through graphs of log returns for each market according to the author's own computations and modeling.Considerable deviations from the mean are evident in the African countries compared to the S & P500. Premised on the afore-mentioned, a development of stock price prediction models that can predict with success in such volatile times will enable investors and other market players to greatly maximize on profitability.

In addition, African stock markets are disparate and exhibit different characteristics as shown in Table 5.1 below which assesses the stock markets on the basis of year of stock market establishment, listings and market capitalization.

TABLE 5.1: African Stock markets' Characteristics

Index	Index Code	Country	Year established	Age	Listings	Market Capitalisation
Botswana Stock Exchange	BGSMDC	Botswana	1989	29	44	USD4.6 B
Egypt Stock Exchange	MXEG	Egypt	1883	135	833	USD7.81B
Nairobi Stock Exchange	NSEASI	Kenya	1954	64	64	USD25.27B
Stock Exchange of Mauritius	SEMDEX	Mauritius	1988	30	170	USD 7.61B
Morocco Stock Exchange	MOSENEW	Morocco	1929	89	81	USD72.58B
Nigeria Stock Exchange	NGSEINDX	Nigeria	1960	58	223	USD41.32B
Johannesburg Stock Exchange	JALSH	South Africa	1887	131	402	USD1.05T
Tunisia Stock Exchange	TUSISE	Tunisia	1969	49	56	USD 7.95B
Lusaka Stock Exchange	LUSEIDX	Zambia	1994	24	16	USD38.93B
Zimbabwe Stock Exchange	ZHINDUSD	Zimbabwe	1948	70	64	USD34.99B
Average	-	-	-	68	195	USD34.6B

[1]Botswana, Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tunisia, Zambia and Zimbabwe

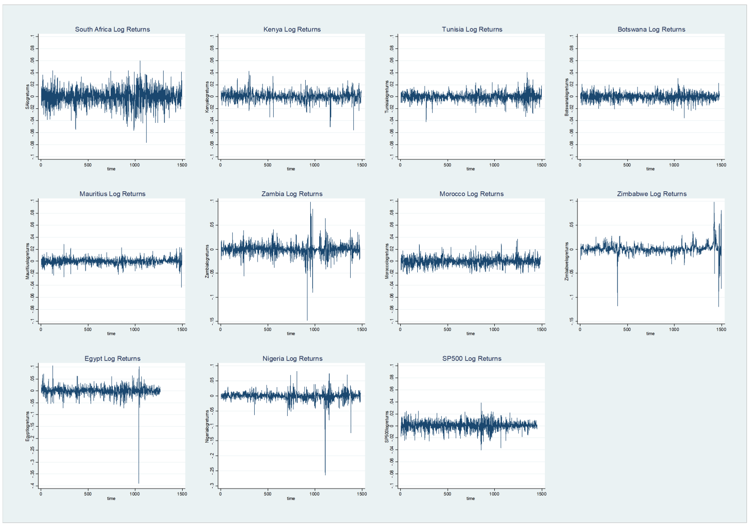

FIGURE 5.2: Volatility of Selected African Markets and S& P500

First, the markets differ regards the year of establishment. The longest surviving bourses are Egypt and Johannesburg stock exchanges with 135 and 131 years of existence to date. Egypt and Johannesburg stock exchanges have the largest listings of 833 and 402 respectively. The Johannesburg Stock exchange outperforms all the other stock markets in this study by having the largest capitalization. The average time of existence for the selected ten sub-Saharan African markets is 68 years with 195 listings and a capitalization of USD34.61 billion. It can be noted from Table 5.1 that Egypt, Morocco, South Africa and Zimbabwe are the only countries that surpass the average years of existence. In addition, Egypt, Mauritius, Nigeria and South Africa are the only countries that have listings above the average of 195 listings per bourse. With regards to capitalization levels, Morocco, Nigeria, South Africa, Zambia and Zimbabwe surpass the average capitalization levels of USD 34.6 billion.

This current research uses absolute stock prices for prediction as motivated by the following studies: (Chen and Wang, 2015; Ma et al., 2015; Laboissiere et al., 2015; Chen and Lee, 2015; Taveeapiradeecharoen et al., 2014; Ticknor, 2013; Kazem et al., 2013). The absolute prices are in the form of open, high, low, close and volume prices. (Chen and Wang, 2015) worked with daily data over 6 years from five stock market indices namely USA's NASDAQ, China Shanghai Composite Index, Hongkong Hang Seng Index, German DAX index and Japan Nikkei 225 index and (Ma et al., 2015) used 5 financial attributes namely the opening, lowest, highest, volume and closing prices to conduct financial predictions.

5.4 Predicting African Stock Markets Using Different Algorithms

5.4.1 Statistical Models

GAM is a statistical approach for nonparametric or semi parametric modeling and it has demonstrated its ability to capture nonlinear relationships between explanatory variables and response variables (Hastie and Tibshirani, 1986), 1986). It is for this reason that this statistical model, GAM, is compared to neural networks to determine if it could predict data nonlinearity with much success. The following steps were undertaken to build the GAM predictive model.

TABLE 5.2: Six Steps in Designing a GAM Forecasting Model

Step 1: Importation of Libraries
Step 2: Data Uploading and formatting according to GAM prophet format
Step 3: Modeling holidays
Step 4: Model fitting
Step 5: Validating the model
Step 6: Backfitting the Algorithm and Evaluation

The initial step in GAM modeling as shown in Table 5.2 above involves importation of all the relevant python 3.6 libraries to start off the model. These include pandas, numpy, statsmodels, matplotlib, scipy, datetime and fbprophet libraries. This step is followed by the uploading of data and formatting it according to GAM prophet format.

Data is loaded in comma separated values (csv) file format for all the parameters. Here, date is converted to date series (ds) and the closing price is set to be the y target (dependent target). The first condition for successful GAM prediction is to change ds into a date time format. This is done so as to read the trend overtime capturing all temporal and long-term dependencies. Closing prices are also logged as a dimensionality reduction initiative. FB Prophet Package allows for specifying different types of functions that comprise the resulting GAM trend. The functions encompass overall growth which is modelled using the default linear growth model; seasonal variations modelled using Fourier analysis to take care of periodic effects and special events (once off events).

Once the data have been uploaded, formatted accordingly and after seasonal decomposition, the GAM model is trained to take into account, trends, seasonalities and holidays. The impact of various anomalies (January effect, week effect, holiday effect etc) on the time series is often similar year after year and can change over time (Plastun et al., 2019b, 2020; Chen and Daves, 2018; Zhang et al., 2017a; Norvaisiene et al., 2015), so it is important to incorporate them into the forecast. Model fitting follows and is done through the stan package. The financial time series is decomposed into three components namely trend, seasonality, and holidays and expressed as follows;

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

where g(t) is the trend function modeling non-periodic changes in the value of the time series, s(t) represents periodic changes (e.g., weekly and yearly seasonality), and h(t) represents the effects of holidays which occur on potentially irregular schedules over one or more days. The error term t represents any idiosyncratic changes which are not accommodated by the model. The forecasting problem is framed as a curve-fitting exercise, which is inherently different from time series models that explicitly account for the temporal dependence structure in the data. An important benefit of the decomposable model is that it allows us to look at each component of the forecast separately.

The horizon or forecasting period for this model was pegged at 365 days. The model predicts stock prices for the next year. A confidence interval of 95% is embedded in the model; therefore, GAM results will be assessed on 5% significance level. Automatic check points are also included in the model to show major events that defined the trend or turning points.

It is important to validate the model after the forecasting exercise. A procedure called simulated historical forecasts (SHF) is used to generate historical forecast errors to fit this model. SHFs are used to produce k forecasts at various cut off points in the history. The SHF procedure is an adaption from the 'rolling origin' forecast evaluation procedures. SHF slices data into time segments across the forecasting horizon instead of sampling data points across time. Each segment is used to predict values in the subsequent year. For instance, in this research, HSF was segmented into twelve (12) time periods over the forecasting horizon.

The model is then back fitted to assess model fitness. Mean prediction error plots are then produced and model is evaluated on MAD, MSE, RMSE, MAPE and Accuracy. Forecast results are reported in three forecast bandwidths namely predicted closing price, upper predicted closing price and lower predicted closing price. The upper and lower predicted prices are linked to the notion of resistance and support levels and can be used to formulate trading strategies. If prices cross the upper predicted price, it is considered a sell signal and if prices crosses the lower predicted price, it is considered a buy signal. This strategy is called a contrarian strategy whereby the upper price is used as resistance in an upward trend and the lower price is used as support in a downtrend. Therefore, GAM prediction results can be used by traders to formulate trading strategies.

5.4.2 Machine Learning Prediction Algorithms

This research was premised on the use of deep neural networks to stock market prediction and settled for the following deep neural networks; LSTM, RNN, GRU, BLSTM, BRNN and BGRU. Previous studies on the use of DNNs for stock price prediction have relied on the use of unidirectional models such as LSTM, RNN and GRU whilst some studies made use bidirectional models (Huynh et al., 2017; Minh et al., 2018).

(Huynh et al., 2017) implemented a BGRU to the S&P 500 achieving a prediction accuracy of nearly 60% for the index whilst (Minh et al., 2018)implemented a two stream gated recurrent unit on the S P500 and achieved an accuracy of 66.32%. Unlike (Huynh et al., 2017) study, this study took a comprehensive usefulness test of more bidirectional architectures to stock price forecasting to include BLSTM and BRNN in addition to the unidirectional models namely RNN, LSTM and GRU. This is the first study to introduce and implement a comprehensive comparison between unidirectional and bidirectional models to stock market predictions. A comparison amongst these architectures was done for the eleven stock markets to ascertain prediction accuracy. These DNNs were also compared to the statistical approach GAM to ascertain if DNNs have superior prediction power over statistical approaches.

Deep Neural Networks

This section of the methodology is guided by the steps or procedures that follow:

The first step of uploading libraries involves the use of the following python 3.6 packages for the implementation of the deep neural network models; numpy,

TABLE 5.3: Six Steps in Designing a Deep Neural Network Forecasting Model

Step 1: Uploading of Libraries
Step 2: Data uploading and Exploratory Data Analysis
Step 3: Data Preprocessing
Step 4: Model Built
Step 5: Training and Validation of Network
Step 6: Evaluation Criteria

matplotlib, pandas, math, time, datetime, itertools, sklearn preprocessing, operator itemgetter, sklearn metrics, keras.models sequential, keras.layers dense, dropout and activation, sklearn minmax scaler and preprocessing. A few commands will vary according to the algorithm being used whether it is unidirectional or bidirectional. An extract of the program code is as follows;

```
In [1]:

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import math, time
from pandas import datetime
import itertools
from sklearn import preprocessing
import    datetime
from operator import itemgetter
from sklearn.metrics import mean_squared_error
from math import sqrt
from pandas.plotting import scatter_matrix
from keras.models import Sequential
from keras.layers.core import Dense, Dropout, Activation
from kera    s.layers import SimpleRNN
from keras.layers import Bidirectional
from sklearn.preprocessing import MinMaxScaler
from keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
from scipy import stats
```

Data uploading is the next step. Each stock market's stock index data is uploaded in csv file format and converted into a data frame format to enable pandas operations to work. The models use only five inputs namely open price, low price, high price, volume and closing price (OHLCV) in order to predict the next day's closing price. These variables are chosen on the basis of previous experiments that use OHLCV data for predictions. The regression formula to examine the above relationship is as follows;

$$Close_{t+1} = f(Open_t, High_t, Low_t, Volume_t, Close_t)$$

After data uploading, the next stage is exploratory data analysis. The motive behind exploratory data analysis (EDA) is to analyze data and their main characteristics in a visual manner. An EDA was conducted and the following were generated; scatter matrix, correlation heatmap, box whisker plots, density plots and histograms.

Getting to know the experiment data is a necessary preliminary evidentiary step in scientific inquiry.

The graphs and charts below in Figure 5.3- 5.7 show histograms, density plots, box and whisker plots, scatter diagrams and a correlation heatmap respectively for the Botswana Stock Exchange. EDA is done for all the stock markets. The plots suggest that volume is not correlated to closing price whilst all the other input variables show a positive correlation to closing price. With such insights, the researcher was prompted to discover if volume had no impact on closing price movements by conducting further analysis in the research. It is important that when analysing these graphs and charts, that each chart or graph be analysed not in isolation to others or other relevant information. The visualisation aspect of the graphs and charts informs a researcher on key issues to focus on.

The histograms are showing that open, high, low and closing prices have a normal distribution whilst the volume distribution is exponential. This is supported by the density plots which show the same distributions. The box and whisker plots present an idea of the spread of the data and dots outside the whiskers show candidate outlier values. Caution must be taken not to conclude analysis on these graphs alone owing to the fact that they are based on absolute prices which are not normalised. Volume values are skewed towards smaller values. The correlation heatmap shows relationships between variables.

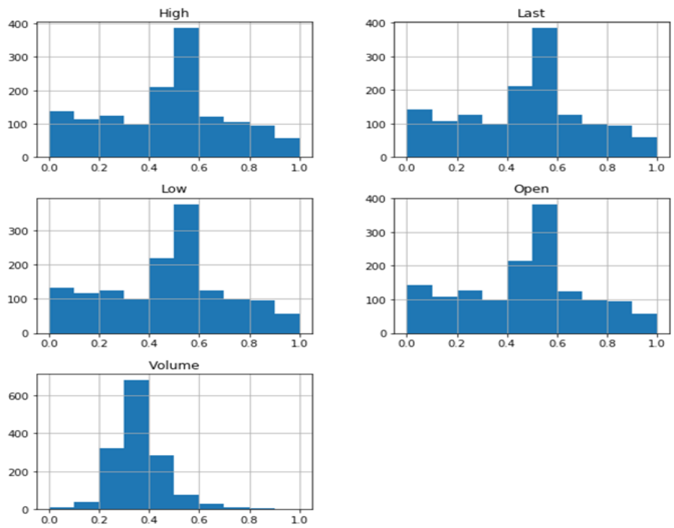

FIGURE 5.3: Histograms for Botswana Input Variables

In an endeavour to minimize the noise in financial data and improving prediction accuracy, it is vital that the collected data be pre-processed, that is, it must be appropriately tuned and normalized at the start of the modeling process (Wang et al., 2015). Stock index data is normalized using the MinMax Scaler function. The features are scaled in the range (0, 1). Normalization is often done to maintain a large variation of prediction and avoid having features with big values over dominate other features. The MinMax Scaler method is chosen over standardization and other techniques as it results in smaller deviations which are likely to restrain the effect of outliers (Raschka, 2014).

In addition, normalization is done owing to the fact that neural networks are known to be sensitive to unnormalised input data to the prediction model (Khare

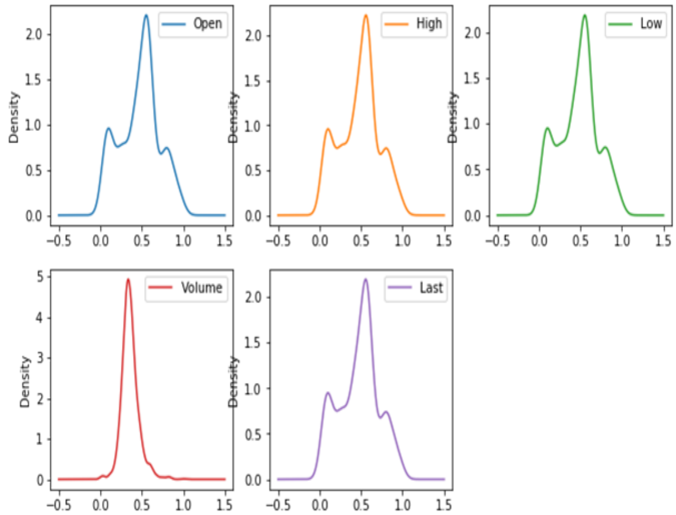

FIGURE 5.4: Density Plots for Botswana Input Variables

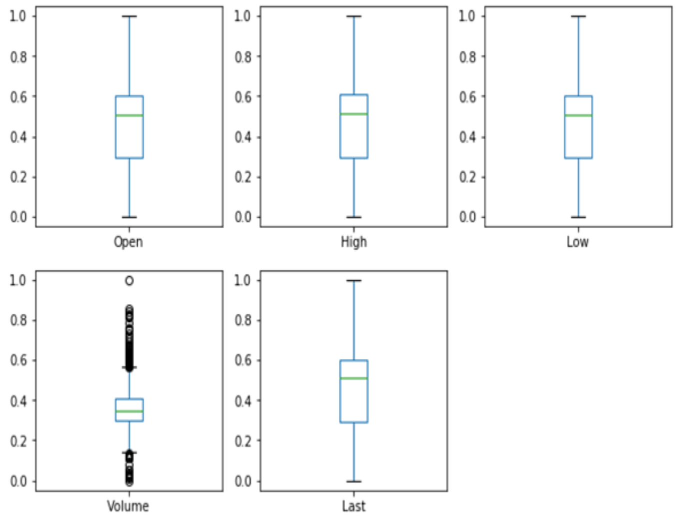

FIGURE 5.5: Box and Whisker Plots for Botswana Input Variables

et al., 2017). The MinMAx normalization helps in improving the speed of convergence and approximation accuracy of the neural network (Guo et al., 2017). The MinMax Scaler estimation technique is determined as follows;

$$X_{std} = \frac{X - X.min(axis=0)}{X.max(axis=0) - X.min(axis=0))}$$

Where $X_{std} = thestandardizedvalue$;
X.min (axis=0) = the smallest value within the data set;
X.max (axis=0) = the largest value within the data set;
X = is the actual data

The formula for normalization is determined by the difference between the actual value and minimum value all divided by the difference between the maximum and minimum value. Herewith is an example of normalized data extract for Botswana Stock Exchange in which the normalised data tells a better picture of the data used than as shown through EDA graphs:

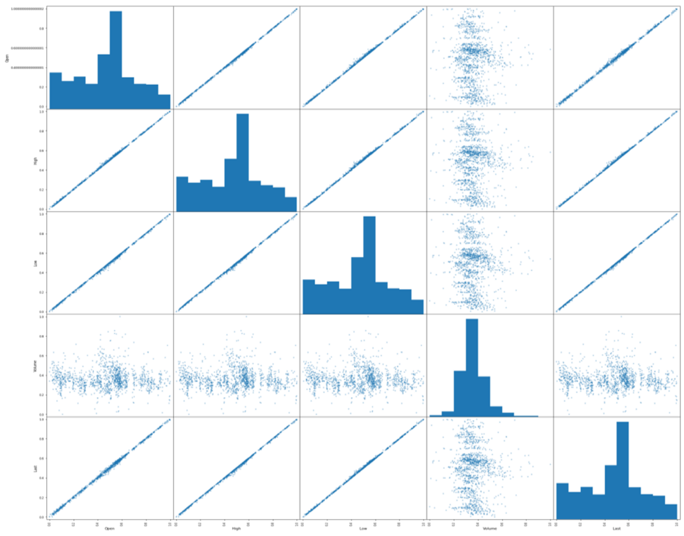

FIGURE 5.6: Scatter Plots for Botswana Input Variables

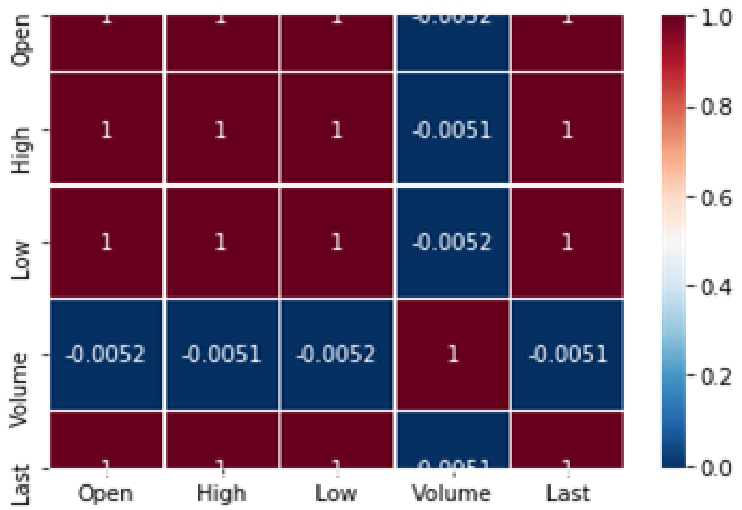

FIGURE 5.7: Correlation HeatMap for Botswana Input Variables

In pursuit of obtaining the true value after the forecasting, the output variable can be reverted back as follows;

$$X_{scaled} = X_{std} * (X.max - X.min) + X.min$$

All the input and output parameters (Open, High, Low, Volume and Closing Price) are normalized between the range (0, 1).

In sample and out sample were considered in this research. An 80/20 split between the in-sample and out-sample was considered. This was premised on Granger's (1993) work where he postulated that a need to retain at least 20% of sample as out of sample and 80% as training set is important. The splits between training and test samples for the eleven stock markets are exhibited in Table 5.5 below. As a rule of thumb, a minimum of 1000 data points for experiments is acceptable; hence all the stock markets meet these criteria.

TABLE 5.4: Normalized Data for Botswana Stock Exchange

Date	Open	High	Low	Volume	Last
2012-04-01	0.350607	0.362134	0.350607	0.006312	0.362134
2012-05-01	0.339795	0.351513	0.339795	0.002192	0.351513
2012-06-01	0.341712	0.353397	0.341712	0.002623	0.353397
2012-09-01	0.330731	0.342610	0.330731	0.001278	0.342610
2012-10-01	0.349611	0.361156	0.349611	0.001663	0.361156
2012-11-01	0.344774	0.356404	0.344774	0.001356	0.356404
2012-12-01	0.368757	0.379961	0.368757	0.009029	0.379961
2012-01-13	0.329982	0.341875	0.329982	0.004322	0.341875
2012-01-16	0.339873	0.351590	0.339873	0.000436	0.351590

TABLE 5.5: Stock Market Application Period and Sample Splits

Index	Country	Start Date	End Date	Data Points	Training set	Test Set
Botswana Stock Exchange	Botswana	2012-01-04	2017-12-29	1452	1162	290
Egypt Stock Exchange	Egypt	2012-01-04	2017-12-29	1242	994	248
Nairobi Stock Exchange	Kenya	2012-01-04	2017-12-29	1466	1173	293
Stock Exchange of Mauritius	Mauritius	2012-01-04	2017-12-29	1528	1222	306
Morocco Stock Exchange	Morocco	2012-01-04	2017-12-29	1465	1172	293
Nigeria Stock Exchange	Nigeria	2012-01-04	2017-12-29	1461	1169	292
Johannesburg Stock Exchange	South Africa	2012-01-04	2017-12-29	1474	1179	295
Tunisia Stock Exchange	Tunisia	2012-01-04	2017-12-29	1473	1178	295
Lusaka Stock Exchange	Zambia	2012-01-04	2017-12-29	1456	1165	291
Zimbabwe Stock Exchange	Zimbabwe	2012-01-04	2017-12-29	1471	1177	294
Standard and Poor's 500	United States of America	2012-01-04	2017-12-29	1508	1206	302

The fourth step is model built up. The model for this research is similar to that of (Huynh et al., 2017). It has the same number of smart neurons or memory units, which are 128. The dropout rate is pegged similarly at 0.2 and it also compares LSTM, GRU and BGRU. Overfitting happens when a function is too closely fit to a limited set of data points and to manage this error type, this study resorted to the use of a drop out layer. Drop out is important as an explicit regularisation technique since it drops certain nodes in the network in an attempt to bring in noise in the data such that the network does not overfit to the data. Drop out is also implemented to ensure improved generalizability.

The model for this research improves on (Huynh et al., 2017) study by extending comparison to include RNN, LSTM, GRU, BRNN, BLSTM and BGRU, encompasses early stopping to avoid overfitting in addition to the dropout layer and adopts a cross-stock market analysis focusing on the S & P500 and ten African markets, which is a cross stock market analysis for the developed, emerging and frontier markets. Early stopping is implemented to stop network training once the error ceases to drop on validation samples. The model for this study is shown in Figure 5.8 below as follows:

Input parameters are open, high, low and close prices together with volume, whilst the output parameter is the closing price for the next day. In other words, the predicted closing price for period t is influenced by previous historical prices. The above architecture will be held constant for comparison purposes for all deep neural networks. Hidden units per layer were pegged at 128. As for bidirectional models, the hidden layer for the second layer consists of 256 (128*2) hidden units

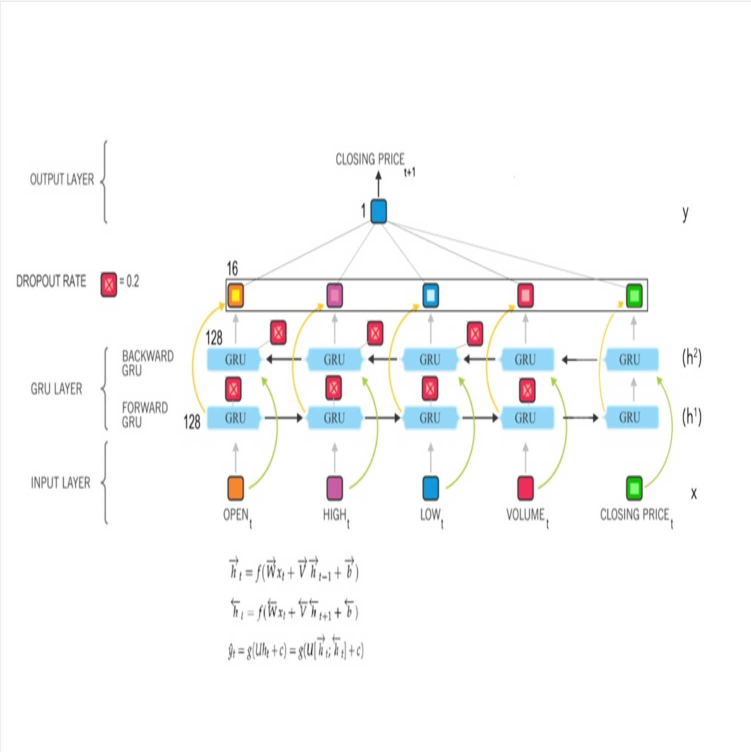

FIGURE 5.8: Prediction Model

as a result of a forward and backward layer. The initializer function considered for this current research was a uniform initializer that derives values from the uniform distribution of data used in this study. The rectified linear unit (Relu) which is a nonlinear activation function is used for the algorithms. It is mostly used because it does not activate all the neurons at the same time, hence, at a time only a few neurons are activated making the network sparse, efficient and easy for computation.

In addition, the Adam optimizer was adopted for this research on the basis that it has proved to be the best and most used optimizer (Persio and Honchar, 2017). The neural networks were trained for 500 epochs. It has been observed that training on many epochs may cause the deep neural network model to overfit test set and just learn the distribution (Persio and Honchar, 2017). Too many epochs may cause overfitting and perform poorly on the test set. Early stopping was noticeable at the 101 epoch. The drop out was pegged at 20% and batch size of 22 was used in the experiments. The network was fed with data within a sliding window size of 22 (one month stock trading month) to predict one day ahead (short term) and 365 days ahead (long term). This means that the data point at time t was predicted using the previous 22 data points (t-1, t-2, t-22). The model summaries for each of the six (6) algorithms showing its parameter relationships are given below in Tables 5.6 -5.11:

In addition, the model also borrows from the time delay embedding method of phase space reconstruction (Huffaker et al., 2017). All time delay constraints in information infiltration into the financial markets are captured by the backward hidden layer of the model. This makes the bidirectional aspects of the model of great importance. The choice for deep neural networks was initially justified in the speech recognition domain mainly because there is evidence that the context of the whole utterance is used to interpret what is being said rather than a linear interpretation.

TABLE 5.6: RNN

Layer (type)	Output Shape	Param
simple$_r nn_1(SimpleRNN)$	(None, 22, 128)	17152
dropout$_1(Dropout)$	(None, 22, 128)	0
simple$_r nn_2(SimpleRNN)$	(None, 128)	32896
dropout$_2(Dropout)$	(None, 128)	0
dense$_1(Dense)$	(None, 16)	2064
dense$_2(Dense)$	(None, 1)	17
Total params: 52,129		
Trainable params: 52,129		
Non-trainable params: 0		

TABLE 5.7: LSTM

Layer (type)	Output Shape	Param
lstm$_1(LSTM)$	(None, 22, 128)	68608
dropout$_1(Dropout)$	(None, 22, 128)	0
lstm$_2(LSTM)$	(None, 128)	131584
dropout$_2(Dropout)$	(None, 128)	0
dense$_1(Dense)$	(None, 16)	2064
dense$_2(Dense)$	(None, 1)	17
Total params: 202,273		
Trainable params: 202,273		
Non-trainable params: 0		

TABLE 5.8: GRU

Layer (type)	Output Shape	Param
gru$_1(GRU)$	(None, 22, 128)	51456
dropout$_1(Dropout)$	(None, 22, 128)	0
gru$_2(GRU)$	(None, 128)	98688
dropout$_2(Dropout)$	(None, 128)	0
dense$_1(Dense)$	(None, 16)	2064
dense$_2(Dense)$	(None, 1)	17
Total params: 152,225		
Trainable params: 152,225		
Non-trainable params: 0		

The same applies to stock prices mainly because of the following factors: Information Asymmetry, Cointegration and Systemic risk. (Jensen, 1978) believes that the release of information has an effect on the stock price. The timing of this release of information is fundamental to understanding the reasons for use of Deep Bidirectional Recurrent Neural Network Architectures in financial time series prediction. The inclusion of forward and backward pass of states from previous states to future

TABLE 5.9: BRNN

Layer (type)	Output Shape	Param
bidirectional$_1$$(Bidirection)$	(None, 22, 256)	34304
dropout$_1$$(Dropout)$	(None, 22, 256)	0
bidirectional$_2$$(Bidirection)$	(None, 256)	98560
dropout$_2$$(Dropout)$	(None, 256)	0
dense$_1$$(Dense)$	(None, 16)	4112
dense$_2$$(Dense)$	(None, 1)	17
Total params: 136,993		
Trainable params: 136,993		
Non-trainable params: 0		

TABLE 5.10: BLSTM

Layer (type)	Output Shape	Param
bidirectional$_1$$(Bidirection)$	(None, 22, 256)	137216
dropout$_1$$(Dropout)$	(None, 22, 256)	0
bidirectional$_2$$(Bidirection)$	(None, 256)	394240
dropout$_2$$(Dropout)$	(None, 256)	0
dense$_1$$(Dense)$	(None, 16)	4112
dense$_2$$(Dense)$	(None, 1)	17
Total params: 535,585		
Trainable params: 535,585		
Non-trainable params: 0		

TABLE 5.11: BGRU

Layer (type)	Output Shape	Param
bidirectional$_1$$(Bidirection)$	(None, 22, 256)	102912
dropout$_1$$(Dropout)$	(None, 22, 256)	0
bidirectional$_2$$(Bidirection)$	(None, 256)	295680
dropout$_2$$(Dropout)$	(None, 256)	0
dense$_1$$(Dense)$	(None, 16)	4112
dense$_2$$(Dense)$	(None, 1)	17
Total params: 402,721		
Trainable params: 402,721		
Non-trainable params: 0		

states and from future states to previous states capturing events which would otherwise be missed in a unidirectional architecture is the key advantage of bidirectional deep neural networks.

In consideration of two architectures namely a simple RNN and a Bidirectional RNN with inputs $x_{t-1}, x_t, \ldots\ldots$ corresponding to time steps $t_{t-1}, t_t, \ldots\ldots$, hidden states $h^1_{t-1}, h^1_t$for the unidirectional RNN $h^1_{t-1}, h^1_t, h^2_{t-1}, h^2_t$and the release of information $i_{t-1}, i_t, \ldots\ldots$to the market corresponding to the same time steps, the prediction of input x_{t-1} is shown by the brown arrow link to output $\hat{y}_t inFigure5.9below;$

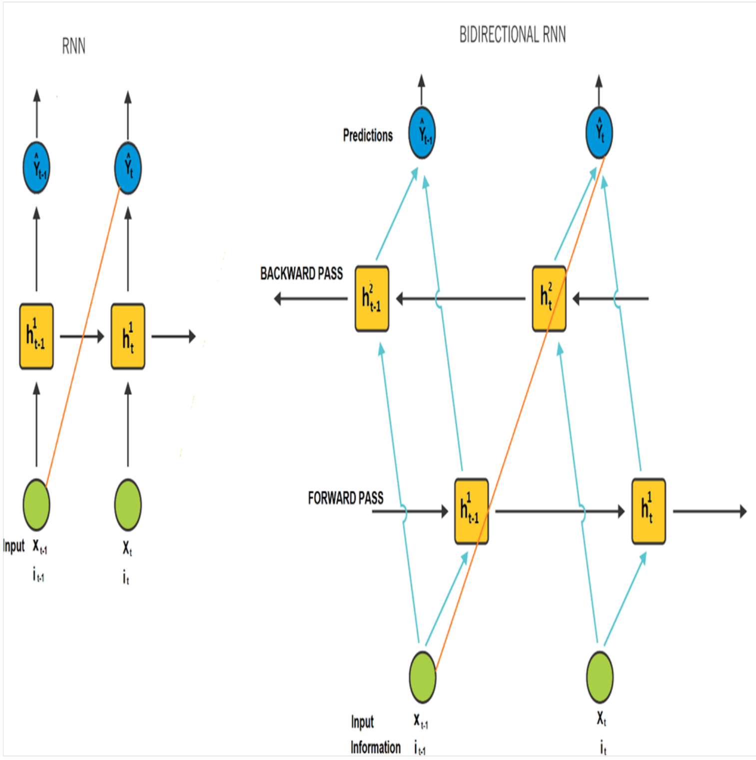

FIGURE 5.9: RNN and BRNN Architecture in Explaining Window Size

As outlined in Figure 5.9, the unidirectional RNN is only able to traverse sequence of states and information from previous states to future states h^1_{t-1}, h^1_t as information arrives. This information which has been captured within the features arrives at each state and influences the prediction of$\hat{y}$ (the future price) at the future state h^1_t. This is in line with the three forms of the EMH namely: weak form EMH, Semi-strong form EMH and Strong Form EMH. This is also in line with the window size of 22, whereby deeper neural networks other than the RNN which suffers from vanishing gradient descent are able to predict outcome using past and future states because of their enhanced memory capacity. With regards to RNNs, they can go far back as three to five days maintaining temporal dependencies. Deeper neural networks with enhanced memory have the ability to capture dependencies for a long time.

Certain risk factors such as systemic risk can be propagated as a contagion effect from various sources such as local and global markets and will impact the stock price at various time intervals due to the fact that this information arrives at different time steps. A simple RNN with a single forward pass will not be able to have all available information in its prediction because it would have missed information that would have been delayed in the previous time step which is captured in the future time step.

A Bidirectional RNN in its backward pass traverses information from future states h^2_t to $h^2_{t_1}$ previous states. This has the effect of including all delayed information into the prediction which otherwise would not have been available in the unidirectional case because information flow is only in fed forward. This now accounts for different information asymmetric events which impact the market at various time steps as the information is released to the public. This also accounts for different systemic risk events, which impact the market at various time steps, as the contagion effect propagates through the market. This also implies that if all things are equal, when information that impacts the markets is not delayed, the unidirectional and bidirectional architecture should yield similar results. According to the financial instability hypothesis (FIH), markets do not provide a natural corrective mechanism, and public intervention should be geared to smoothing systematic boom and bust cycles (Minsky, 1992). This can be guided through bidirectional deep network architectures that are able to capture the chaotic nature of stock markets.

5.5 Training Results for DNN Architectures

The following training results in Table 5.12 were trained on 80% of the sample data and were assessed on two metrics namely MSE and RMSE. The results for all eleven stock market indices reveal good convergence as the error metrics of MSE and RMSE are very low and all close to zero. However, Zambia has a relatively higher error metrics close to 11% as shown in Table 5.20.

TABLE 5.12: Summary of Training Results for Botswana

Algorithm	MSE	RMSE
LSTM	0.0005	0.0234
GRU	0.0009	0.0297
RNN	0.0015	0.0384
BLSTM	0.0009	0.0293
BGRU	0.0013	0.0362
BRNN	0.0006	0.0247

TABLE 5.13: Summary of Training Results for Egypt

Algorithm	MSE	RMSE
LSTM	0.0008	0.0284
GRU	0.0004	0.0197
RNN	0.0003	0.0185
BLSTM	0.0007	0.0255
BGRU	0.0003	0.0184
BRNN	0.0014	0.0378

5.6 Econometric Model

In order to avoiding lumping countries together, a situation in which country specific information may be lost, the use of time series techniques was considered for

TABLE 5.14: Summary of Training Results for Kenya

Algorithm	MSE	RMSE
LSTM	0.0016	0.0402
GRU	0.0005	0.0220
RNN	0.0007	0.0264
BLSTM	0.0003	0.0161
BGRU	0.0001	0.0106
BRNN	0.0002	0.0133

TABLE 5.15: Summary of Training Results for Mauritius

Algorithm	MSE	RMSE
LSTM	0.0004	0.0206
GRU	0.0003	0.0162
RNN	0.0015	0.0387
BLSTM	0.0002	0.0145
BGRU	0.0005	0.0230
BRNN	0.0004	0.0207

TABLE 5.16: Summary of Training Results for Morocco

Algorithm	MSE	RMSE
LSTM	0.0005	0.0227
GRU	0.0002	0.0148
RNN	0.0001	0.0113
BLSTM	0.0020	0.0130
BGRU	0.0001	0.0109
BRNN	0.0001	0.0110

TABLE 5.17: Summary of Training Results for Nigeria

Algorithm	MSE	RMSE
LSTM	0.0004	0.0189
GRU	0.0004	0.0189
RNN	0.0001	0.0112
BLSTM	0.0003	0.0170
BGRU	0.0001	0.0114
BRNN	0.0003	0.0164

this current research (Ho, 2017). A causal research design was adopted for this experiment and assesses the relationship of closing stock prices to various independent variables (money supply, inflation, interest rates and exchange rates) using a macroeconomic variable model.

TABLE 5.18: Summary of Training Results for South Africa

Algorithm	MSE	RMSE
LSTM	0.0007	0.0256
GRU	0.0003	0.0183
RNN	0.0006	0.0240
BLSTM	0.0004	0.0211
BGRU	0.0004	0.0194
BRNN	0.0006	0.0236

TABLE 5.19: Summary of Training Results for Tunisia

Algorithm	MSE	RMSE
LSTM	0.0003	0.0169
GRU	0.0005	0.0214
RNN	0.0003	0.0159
BLSTM	0.0002	0.0154
BGRU	0.0002	0.0142
BRNN	0.0004	0.0200

TABLE 5.20: Summary of Training Results for Zambia

Algorithm	MSE	RMSE
LSTM	0.1174	0.3426
GRU	0.1178	0.3432
RNN	0.1178	0.3482
BLSTM	0.1182	0.3438
BGRU	0.1181	0.3437
BRNN	0.1178	0.3432

TABLE 5.21: Summary of Training Results for Zimbabwe

Algorithm	MSE	RMSE
LSTM	0.0001	0.0091
GRU	0.0001	0.0084
RNN	0.0001	0.0102
BLSTM	0.0001	0.0075
BGRU	0.0001	0.0096
BRNN	0.0001	0.0090

5.6.1 Data

The International Financial Statistics (IFS) database from the International Monetary Fund was used to collect macroeconomic data namely Inflation (proxy used was CPI), interest rates, money supply and exchange rate. Closing index prices were

TABLE 5.22: Summary of Training Results for S&P500

Algorithm	MSE	RMSE
LSTM	0.0002	0.0127
GRU	0.0002	0.0124
RNN	0.0002	0.0135
BLSTM	0.0002	0.0124
BGRU	0.0010	0.0312
BRNN	0.0005	0.0217

obtained through the Bloomberg terminal for the 10 African stock markets. Using time series econometrics, the macroeconomic factors were used to determine which macroeconomic factors significantly influence the index closing stock returns.

Data was collected for the period 2012 to 2017. During this period, at a global scale, the world was affected by global shocks from the Chinese stock market crash in 2016, the winning of Donald Trump in the US elections. These two events around 2016 send economic shock waves across the world, especially to nations that traded with the two countries. Regionally, nations such as South Africa, Nigeria, Botswana and Zambia that deal with the Chinese were greatly affected (Africa Economic Outlook reports, 2012-2017). In addition, various political changes during the 2012-2017 periods saw the 10 African countries under consideration in this research experiencing various shocks on their stock markets. It is thus the intention of the research to forecast stock prices in such volatile environments and understand which factors influence stock price movements in African stock markets. The decision on which macroeconomic variables to use was dependent on data availability. The experiments to determine the relationship between these macroeconomic variables to stock prices based on the ordinary least squares (OLS) were analyzed using Stata 13 and R 3.6 as follows;

$$lnCL = \beta_0 + \beta_{1t} lnCPI + \beta_{2t} LnEXR + \beta_{3t} LnINTR + \beta_{4t} LnM2 + \epsilon_{it}$$

A brief discussion for each adjusted variable used in presented in table 5.23 below.

TABLE 5.23: Lagged Variables

Variable	Concept	Description
ln CL	Natural logarithm of index Closing Price	Country Index
ln CPI	Natural logarithm of consumer prices	Consumer prices
ln EXR	Natural logarithm of exchange rate	official exchange rate
lnM2	Natural logarithm of M2	Money supply
ln INTR	Natural logarithm of interest rate	interest rate

The β_0 is the intercept of the regression representing the risk-free rate as a constant while β_1,β_2 ,β_3 ,β_4 are the coefficient of variables and ϵ_{it} is the error term. All variables were computed on a monthly basis in order to have a standard basis for analysis. All the explanatory variables were selected as guided by literature. The most common determinants of stock prices are inflation (proxied by consumer price index-cpi), money supply, exchange rate and interest rate (Chen and Chen, 2012; Gupta and Inglesi-Lotz, 2012; Cogley and Sargent, 2001; Dhakal et al., 1993).

In addition to the above, the following econometric tests were done using stata 13 and R 3.6 to ascertain the relationship between closing price and macroeconomic variables; unit root tests, vector auto regression, cointegration tests and granger causality test.

5.6.2 Unit root testing

In analyzing economic models, the stationarity of economic time series is of great importance. The use of non-stationary time series data can create spurious regression results which do not permit meaningful inferences. Amongst the most common unit root tests are Dickey Fuller tests (DF), augmented dickey fuller tests (ADF) and the Phillips and Perron test (PP). For the purposes of this study, the ADF is selected since it can model economic time series which is of a mixed auto-regression integrated moving average (ARIMA) process and owing to the potential of time trends in the economic series, ADF becomes the most appropriate unit root testing tool and is modelled as follows;

$$\Delta\gamma_t = \alpha_0 + \alpha_{1t} + \gamma_{yt-1} + \sum_{i=1}^{n} \beta_i \Delta\gamma_{t-1} + \epsilon_t$$

Where y is lnclose (or lnCPI, lnEXR, lnINTR, lnM2), Δ denotes first difference and n is the lag length and t is the trend. The equation is also estimated without trend and different lag lengths are fixed according to the Akaike Information Criteria (AIC).

5.6.3 Order of Integration

The order of integration is then determined to see if the time series contains a unit root. If all the series are integrated of the same order, then cointegration tests can be implemented (Bhuiyan and Chowdhury, 2019). After determination of level of integration, the analysis then proceeds with determination of lag length to be employed in cointegration tests.

5.6.4 Johansen Cointegration Test

This test is to ascertain whether the time series is cointegrated or not. If they are cointegrated, the stable long run relationship between the variables is then implemented and a normal regression can be performed to examine the relationship among them. According to (Bhuiyan and Chowdhury, 2019), cointegration tests are conducted to detect the existences of stable long run relationships between two or more variables. However if the series are not cointegrated, the study will test for short term relationships. The Vector error correction model adopted for the study is as follows;

$$\Delta\ lnClose_t = \alpha_0 + \sum_{i=1}^{n} \beta_{1i} \Delta\ lnclose_{t-1} + \sum_{i=1}^{p} \beta_{2i} \Delta\ lnM2_{t-1} + \sum_{i=1}^{q} \beta_{3i} \Delta\ lnCPI_{t-1} + \sum_{i=1}^{r} \beta_{4i} \Delta\ lnExr_{t-1} + \sum_{i=1}^{s} \beta_{5i} \Delta\ lnINTR_{t-1} + \lambda_t ECT_{t-1} + \epsilon_t$$

Where $\Delta\ lnclose_t$ represents changes in closing price from one period to the next; n, o, p, q, r, s are the number of lag lengths, ECT_{t-1} is the error correction term and the coefficient $_t$ of the error correction term measures the speed of adjustment when there is a deviation from the equilibrium.

5.6.5 Granger Causality

If time series is co-integrated, the granger theorem would imply that the dynamic relations between the variables must be examined within the Vector Error correction model(VECM) framework which captures both the short-run dynamics between time series and their long-run equilibrium relationship. If there is no cointegration, a vector auto regression (VAR) model is implemented.

5.7 Chapter Summary

This chapter focused on the methodology for conducting the experiments for this research. The variables used and parameters used for the prediction algorithms were fully explained and justification for their use was also done. A time series data econometric model was also discussed in this chapter and the reasons for its use. The chapter that follows will focus on the findings from experiments conducted.

Chapter 6

Research Findings

6.1 Introduction

The chapter presents the results of the study and is structured as follows: Section 6.2 presents performance of DNN models in predicting the stock price whilst Section 6.3 presents performance of GAM models in predicting the stock price. Sections 6.4 to 6.12 present graphical representations of the prediction results and the seasonal components of the forecast time series for the respective stock markets with regards to GAM predictions. The chapter also looks at the a summary of the GAM prediction results in section 6.13 and section 6.14 presents time series econometric results before the chapter concluded with a summary.

6.2 Performance of DNN Models in Predicting Stock Market Index Price

In pursuit of developing prediction models that can accurately predict the future closing stock price movements of ten selected African countries stock markets and the S& P500 , this research focused on the use of deep neural models namely RNN, LSTM, GRU, BRNN, BLSTM and BGRU to predict future stock prices. An analysis of the differences between these emerging and frontier markets to the developed markets will be discussed in the sections that follow.

The afore-mentioned algorithms developed for this research were evaluated using five (5) performance metrics namely MAD, MSE, RMSE, MAPE and Accuracy. Lower values for the MAD, MSE, RMSE, MAPE evaluation metrics are considered as the best metrics. With regards to the accuracy metric, the higher the metric, the more desirable it is, with a 100% accuracy being the most ideal as it entails no risk of loss. All metrics in bold revealed the best outcome for each DNN model. The accuracy rate shows the level to which the prediction model was able to predict accurately the next day's closing price. Table 6.1 reports on the combined DNN and GAM prediction accuracy results for the eleven stock market indices and the prediction summaries based on the evaluation metrics for all indices respectively using a machine learning regression approach. The following results are based on the out of sample, i.e. 20% of the data sample.

The results bear evidence of return predictability of financial markets (African stock markets and USA). The developed model for this research was able to learn and predict all the selected stock indices satisfactorily. A common benchmark for the success of any prediction model is that it should surpass the 50% accuracy mark and in this research, all predictions were above this mark.

Both GAM and DNN prediction results attest to the fact that African stock markets have high return predictability characteristics as indicated in (Alagidede, 2011)

TABLE 6.1: Summary of Prediction Accuracy Results

Algorithm Stock Market	**RNN** %	**BRNN** %	**LSTM** %	**BLSTM** %	**GRU** %	**BGRU** %	**GAM** %
Botswana	95.28	95.76	96.05	91.22	95.95	95.59	**99.76**
Egypt	90.05	90.31	92.95	91.50	86.50	91.42	**97.55**
Kenya	71.76	81.00	67.55	68.36	74.51	84.71	**100.00**
Mauritius	97.00	97.01	96.57	97.35	95.43	97.50	**99.21**
Morocco	97.67	97.53	97.70	97.35	97.69	97.74	**99.50**
Nigeria	97.42	96.72	98.96	98.88	98.50	98.65	**99.32**
South Africa	97.36	97.94	97.74	97.66	97.45	97.90	**99.58**
Tunisia	82.53	84.18	97.95	96.25	94.75	95.71	**99.88**
Zambia	76.45	76.32	76.80	75.95	76.27	76.29	**99.59**
Zimbabwe	97.96	97.72	97.66	96.94	95.62	97.46	**99.52**
S&P500	42.65	47.81	59.14	42.08	66.18	66.47	**99.57**

findings on African stock markets. Several factors can give rise to such satisfying predictions. The DNN prediction accuracies attained in this research could be a reflection of stock market inefficiency, low market capitalisation and illiquidity in African stock markets, which can potentially be exploited for financial gain. Return predictability can arise from time to time due to altering economic conditions and institutional factors in market ecology, hence giving rise to different results for each country even though the same prediction models were used (Kim et al., 2011; Charles et al., 2017). African equity markets are receiving increased interest among international investors and can be considered attractive for investment diversification (Kodongo and Ojah, 2014). Therefore, it is imperative for investors (domestic and foreign) to diversify their portfolios by including African stock market stocks in order to maximise their investment gains through the use of the above mentioned prediction models.

In agreement with (Smith, 2008), markets are affected by a variety of characteristics such as the varying number and size of stocks traded, quality of information and the speed at which it is made available to market participants and the institutional characteristics of each market. In addition to these, the age of the market and number of listings could also contribute to the varying efficiency levels of each market. For instance, Zambia has the lowest number of listings and is fairly a young market. As a result, DNN models prediction performance for this market was very low compared to other markets. Also, in information efficient markets such as S& P500, where speed of information flow is high, prediction accuracies and arbitraging opportunities were very low.

However, caution must be taken not to base the various DNN prediction accuracies across markets either to be solely caused by a single factor such as market capitalisation, age of exchange or listings. For the emerging markets of Egypt and South Africa with the highest number in listings and age of markets, prediction accuracy was lower compared to other markets. The respective markets prediction results could be a result that both markets are informationally efficient creating no room for arbitraging and hence, low profit attainment possibilities. This point to the fact that since stock markets behaviour is a sum game of various influencing variables, no single variable is able to explain the varying prediction performances of the algorithms in the eleven stock markets. Such variability in influencing factors can explain why the algorithms performed differently in this cross stock market analysis research. Every market is distinct in its own way and is affected differently by various factors.

Another possible explanation to the attainment of such results when compared to the S& P500 and in agreement with (Alagidede, 2011) is that African markets suffer from several imperfections such as absence of accurate legal and regulatory frameworks, have undeveloped financial systems and the existence of stylized facts such as low trading volumes, low liquidity and low turnover. The underdevelopment of legal and information systems is noted to have an effect on the price discovery process and hinder the speed at which new information can be reflected in prices, and or become public.

In addition, if the regulatory framework for stock exchanges does not allow investors to freely transact so that shares can be transferred across markets with ease, the implication of such systems is that the markets suffer from liquidity and informational efficiencies. For example, the Zimbabwe stock exchange suffers from low stock/share fungability. For dual listed shares, approval should be sought from authorities to sell shares bought in another country or shares purchased in Zimbabwe in another country. Such regulatory issues affect overall market liquidity. Liquidity facilitates the price formation process. Opportunities for prices to change in response to new information results from more frequent trading and thus can make a market to be weak form efficient. Therefore, illiquid or low liquid markets are preferable candidates for stock prediction.

Frontier stock markets inclusive of the Moroccan financial market are characterised by a narrowness of the market, inability to absorb erratic price fluctuations and the low liquidity of securities encourage investor herd behavior as they imitate those who are believed to have all information about the market (Mustapha and Ahmed, 2019). Results in Table 6.1 show the high predictive power of algorithmic predictive financial models for frontier markets including Morrocco which investors can adopt for trading strategy formulation other than to rely on other investors for the investment decision making process, hence reducing behavioural biases.

Another notable fact from Table 6.1 is that GAM prediction results outperformed all DNN predictions. These findings concur with (Shan et al., 2015) view that at times statistical techniques super- cede ANNs. The evidence from these results is thus in contrast with various studies by (Reid et al., 2014), and (Ma et al., 2015) which concluded that ANNs represented in this study by DNNs are better prediction tools as compared to statistical techniques. As evidenced in Table 6.1, it can be noted that financial time series modelling for stock markets (developed, developing, emerging or frontier) through statistical machine learning techniques yields better results as compared to deep neural network machine learning techniques. Overall, predictions performances in Table 6.1 outperformed experimental results from other research studies. The DNN and GAM prediction results greatly improved on prediction accuracy for the African stock markets and for the S&P500 when compared to prior research studies shown in Table 6.2.

The key implication to such findings is that investors can make use of the DNN and GAM prediction models for asset pricing and investment decisions. Thus they can be able to earn huge profits through the use of algorithmic finance initiatives. Other key findings for this research note that GAM outperformed all DNN algorithms and that amongst the DNN algorithms used for this research, LSTM was overall the best algorithm for prediction in Sub-Saharan African stock markets. This buttresses the fact by (Graves and Schmidhuber, 2006)that deep layered LSTM architectures are able to build up progressively higher levels of representation of sequence data.

In cases where bidirectional LSTM architectures outperformed LSTM as in Kenya, Mauritius and Zimbabwe, there was not any outstanding change between LSTM

TABLE 6.2: Stock Market Predictions

Author(s)	Year	Stock Market	Prediction Technique	Accuracy (%)
Osama and Dina	2017	Egypt	Technical Analysis	85.50
Isenah and Olubusoye	2014	Nigeria	ANN	45.46
Lin et al	2020	S&P500	RNN-ZCR	60.00
Minh et al	2018	S&P500	Two Stream GRU	66.32
Huynh et al	2017	S&P500	LSTM	58.64
-	-	-	GRU	58.59
-	-	-	BGRU	59.98
Oncharoen and Vateekul	2018	S&P500	Alpha based Values	62.27
-	-	-	Beta based values	65.08

and BLSTM results. This reinforces the fact that although there is a variety of LSTM variants, none of the variants can improve upon the standard LSTM architecture significantly (Greff et al., 2017). Results between LSTM and GRU also show superiority in prediction power of LSTM over GRU. The LSTM also outperforms BLSTM, hence disproving (Graves and Schmidhuber, 2006) claim that for sequence modelling, BLSTM has more advantage than LSTM. Experiment results for this research show that the LSTM outweighs BLSTM.

The afore-mentioned observations were different for the BGRU and BRNN. The BGRU outperformed GRU and BRNN outperformed RNN. This research results are in support of (Khandelwal et al., 2017)sentiment that BRNN perform better than RNN. GRUs also performs better than RNN is most experiments. However, this view is in contrast to Amodei et al., (2015) whom opined that simple RNN perform slightly better than GRUs. Bidirectional architectures have the advantage of capturing delayed historical information in the asset pricing process as it back propagates in the reverse direction. This may be a reason for better performance of the BGRU and BRNN in comparison to their unidirectional architectures. In addition, owing to the various calendar anomalies, different trading behaviour of investors in the different African stock markets and varying microstructure characteristics, the algorithms performed differently in each stock market. However, the LSTM and BGRU were the best prediction algorithms for the African markets and the S&P500. This finding brings new prediction evidence to the fact that LSTMs are also suitable for predicting high volatility stocks inherent in most African stock market indices. this contradicts (Jeenanunta et al., 2018) findings that LSTMs work well for low volatility stocks.

In another study by (Chung et al., 2014), it was found out that LSTM and GRU significantly outweighed tanh models. However, there was no concrete conclusion to which architecture between LSTM and GRU performs better than the other. (Huynh et al., 2017) experimented on the S&P 500 and found out that LSTM outperforms GRU. Corroborating to these findings are this current research findings where evidence of LSTM outperforming GRU in the African stock markets is present.

A similarity to (Huynh et al., 2017) study to this research is that there was no remarkable change in prediction accuracy between LSTM, GRU and BGRU with accuracy levels of 59.14%, 66.18% and 66.47% for LSTM, GRU and BGRU respectively for the S& P500 in this research.Hoewver, the results attained in this current study outperform those attained by (Huynh et al., 2017) in which LSTM, GRU and BGRU had 58.64%,58.59% and 59.98% accuracy levels respectively. In addition, this current research also found out that BGRU outperformed the LSTM and GRU respectively for the S& P500 and other African stock markets as was observable in the (Huynh et al., 2017) study.

The prediction models for this research produced better results for the African stock markets when compared to the benchmark S& P500. This could have been a result of the inefficiency of African markets giving rise to the possibility of beating the markets. As for the S&P 500 which is regarded as efficient, liquid and a developed market, prediction results were lower than those for the selected African inefficient stock markets.The models presented interesting results which outperformed (Huynh et al., 2017; Lin et al., 2020; Minh et al., 2018), results. In addition to the three models used in (Huynh et al., 2017) study, this current research extended the bouquet of financial prediction models to include BLSTM, RNN and BRNN and obtained 42.08%, 42.65% and 47.81% accuracy levels for the S&P500 and satisfactory results for the African stock markets. Figure 6.3 to 6.13 provides the test prediction results for the eleven indices measured on MAD, MSE, RMSE and MAPE.

TABLE 6.3: Summary of Prediction Results for Botswana

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.0184	0.0006	0.0236	4.0700
BLSTM	0.0448	0.0026	0.0505	9.8893
GRU	0.0189	0.0006	0.0240	4.2046
BGRU	0.0209	0.0007	0.0264	4.6777
RNN	0.0219	0.0008	0.0276	4.7907
BRNN	0.0200	0.0007	0.0256	4.4394
GAM	**0.0162**	**0.0003**	**0.0183**	**0.2372**

TABLE 6.4: Summary of Prediction Results for Egypt

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	**0.0171**	**0.0008**	**0.0280**	217.1033
BLSTM	0.0289	0.0045	0.0670	754.5221
GRU	0.0428	0.0036	0.0604	255.8491
BGRU	0.0288	0.0016	0.0396	220.1876
RNN	0.0276	0.0014	0.0371	238.3662
BRNN	0.0273	0.0011	0.0337	238.3662
GAM	0.1258	0.0255	0.1596	**2.5489**

The research results point to the effectiveness of GAM, BGRU and LSTM as the best prediction models for African stock markets. However in overall, GAM had the best results . For the S&P 500, the BGRU, GRU and LSTM are the best performing algorithms. When prediction accuracy analysis is done only for DNNs, the LSTM is the best prediction model for the African markets followed by the BGRU which is superior to BRNN and RNN algorithms respectively. The proposed RNN prediction model results for Morocco are better than those found in (Berradi and Lazaar, 2019)study based on MSE. In support of the afore-mentioned results for the DNN evaluation only, Table 6.14 below reports on sample empirical results for each best algorithm per stock market. Y and Yhat represent actual and predicted values whilst

TABLE 6.5: Summary of Prediction Results for Kenya

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.1610	0.0303	0.1741	312.0933
BLSTM	0.1064	0.0298	0.1728	341.6809
GRU	0.0506	0.0051	0.0713	133.1530
BGRU	**0.0212**	**0.0012**	**0.0343**	70.8493
RNN	0.1353	0.0226	0.1502	280.6767
BRNN	0.0296	0.0016	0.0395	71.4517
GAM	0.0314	0.0012	0.0343	**14.4388**

TABLE 6.6: Summary of Prediction Results for Mauritius

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.0142	0.0003	0.0182	3.6341
BLSTM	0.0107	0.0002	0.0144	2.7220
GRU	0.0200	0.0006	0.0238	4.8789
BGRU	**0.0101**	**0.0002**	**0.0139**	2.5591
RNN	0.0125	0.0003	0.0165	3.1261
BRNN	0.0122	0.0003	0.0161	3.1118
GAM	0.0325	0.0011	0.0330	**0.7836**

TABLE 6.7: Summary of Prediction Results for Morocco

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.0129	0.0003	0.0162	2.3690
BLSTM	0.0148	0.0003	0.0185	2.7459
GRU	0.0132	0.0003	0.0169	2.3179
BGRU	**0.0127**	**0.0003**	**0.0158**	2.3316
RNN	0.0167	0.0004	0.0205	2.3935
BRNN	0.0144	0.0004	0.0198	2.5425
GAM	0.0360	0.0019	0.0439	**0.5028**

TABLE 6.8: Summary of Prediction Results for Nigeria

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	**0.0040**	**0.0000**	**0.0052**	1.0463
BLSTM	0.0049	0.0000	0.0070	1.1342
GRU	0.0067	0.0001	0.0094	1.5305
BGRU	0.0062	0.0001	0.0084	1.3729
RNN	0.0101	0.0001	0.0115	2.5796
BRNN	0.0129	0.0002	0.0156	3.3080
GAM	0.0333	0.0013	0.0350	**0.6866**

TABLE 6.9: Summary of Prediction Results for South Africa

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.0160	0.0004	0.0203	2.2951
BLSTM	0.0166	0.0004	0.0210	2.3752
GRU	0.0183	0.0005	0.0222	2.6414
BGRU	0.0148	0.0004	0.0188	2.1312
RNN	0.0162	0.0005	0.0229	2.6789
BRNN	**0.0000**	**0.0003**	**0.0185**	2.1056
GAM	0.0353	0.0022	0.0473	**0.4234**

TABLE 6.10: Summary of Prediction Results for Tunisia

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.0168	0.0005	0.0222	2.0591
BLSTM	0.0315	0.0017	0.0410	3.7594
GRU	0.0426	0.0022	0.0472	5.2140
BGRU	0.0358	0.0019	0.0436	4.2927
RNN	0.1432	0.0251	0.1584	17.4728
BRNN	0.1314	0.0023	0.1512	15.8172
GAM	**0.0095**	**0.0001**	**0.0126**	**0.1187**

TABLE 6.11: Summary of Prediction Results for Zambia

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.1249	0.0184	0.1355	23.1971
BLSTM	0.1293	0.0195	0.1396	24.0527
GRU	0.1277	0.0191	0.1381	23.7338
BGRU	0.1275	0.0190	0.1379	23.7068
RNN	0.1267	0.0188	0.1372	23.5506
BRNN	0.127	0.019	0.138	23.680
GAM	**0.027**	**0.001**	**0.031**	**0.403**

TABLE 6.12: Summary of Prediction Results for Zimbabwe

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.0031	0.0000	0.0044	2.4120
BLSTM	0.0037	0.0000	0.0048	3.1216
GRU	0.0063	0.0001	0.0084	4.6319
BGRU	0.0034	0.0000	0.0048	2.6343
RNN	**0.0025**	**0.0000**	**0.0033**	2.0929
BRNN	0.0027	0.0000	0.0035	2.2864
GAM	0.0239	0.0009	0.0265	**0.4836**

TABLE 6.13: Summary of Prediction Results for S& P500

Algorithm	MAD	MSE	RMSE	MAPE
LSTM	0.0737	0.0072	0.0846	130.8674
BLSTM	0.1455	0.0216	0.1470	195.1936
GRU	0.0512	0.0038	0.0618	96.7830
BGRU	0.0493	0.0031	0.0559	89.0533
RNN	0.1584	0.0289	0.1701	251.8089
BRNN	0.1142	0.0160	0.1265	151.4058
GAM	**0.0309**	**0.0015**	**0.0381**	**0.4275**

Diff is the absolute difference between actual and predicted. Also included in the table are the Z-score and P-values. The sample empirical results are for the first ten predicted values.

TABLE 6.14: Summary Prediction Results for Botswana Stock Exchange- LSTM

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.546407	0.560747	0.01434	-0.271885	0.785711
1	0.548503	0.546477	0.002026	-1.100972	0.270909
2	0.542317	0.547171	0.004853	-0.91061	0.362501
3	0.5391	0.540584	0.001484	-1.137424	0.255361
4	0.566739	0.536432	0.030307	0.80307	0.421934
5	0.589732	0.562269	0.027463	0.611589	0.54081
6	0.579844	0.582288	0.002444	-1.072801	0.28336
7	0.591853	0.571651	0.020202	0.122786	0.902276
8	0.566022	0.58635	0.020328	0.131226	0.895596
9	0.556086	0.562887	0.006801	-0.779459	0.435709

TABLE 6.15: Summary Prediction Results for Egypt Stock Exchange- LSTMM

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.398149	0.390703	0.007446	-0.436303	0.662617
1	0.368575	0.400699	0.032124	0.636002	0.524775
2	0.368842	0.358021	0.010821	-0.28966	0.772076
3	0.379707	0.363636	0.016071	-0.061521	0.950945
4	0.346707	0.370451	0.023743	0.271867	0.785724
5	0.338741	0.34189	0.003149	-0.623012	0.533277
6	0.305826	0.347354	0.041528	1.044625	0.296196
7	0.305591	0.298952	0.006639	-0.471375	0.637373
8	0.368379	0.315622	0.052757	1.532574	0.125381
9	0.346382	0.378288	0.031906	0.62656	0.530948

TABLE 6.16: Summary Prediction Results for Nairobi Stock Exchange -BGRU

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.418319	0.418911	0.000592	-0.765873	0.443752
1	0.404156	0.419536	0.01538	-0.217593	0.827746
2	0.397118	0.413467	0.016349	-0.181641	0.855865
3	0.392915	0.406389	0.013474	-0.288238	0.773164
4	0.367374	0.400502	0.033128	0.440437	0.659621
5	0.363532	0.382922	0.01939	-0.068923	0.945051
6	0.364607	0.372777	0.00817	-0.484907	0.627742
7	0.3652	0.370954	0.005754	-0.574474	0.565647
8	0.363472	0.371589	0.008116	-0.486891	0.626336
9	0.374739	0.367776	0.006963	-0.52966	0.596348

TABLE 6.17: Summary Prediction Results for Stock Exchange of Mauritius – BGRU

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.562316	0.587314	0.024998	0.384449	0.700645
1	0.556129	0.578889	0.02276	0.210798	0.833045
2	0.551609	0.576334	0.024726	0.363339	0.716351
3	0.540104	0.574807	0.034703	1.137752	0.255224
4	0.554712	0.567417	0.012706	-0.569583	0.56896
5	0.536636	0.567972	0.031336	0.876386	0.38082
6	0.533423	0.55322	0.019797	-0.019192	0.984688
7	0.531879	0.554999	0.023119	0.238672	0.81136
8	0.541419	0.548234	0.006815	-1.026736	0.304545
9	0.510322	0.55741	0.047088	2.098978	0.035819

TABLE 6.18: Summary Prediction Results for Stock Exchange of Morocco – BGRU

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.280517	0.291907	0.01139	-0.133572	0.893741
1	0.303901	0.292039	0.011862	-0.083964	0.933085
2	0.309084	0.322891	0.013807	0.120118	0.90439
3	0.311894	0.315181	0.003287	-0.983935	0.325147
4	0.311148	0.305391	0.005757	-0.724649	0.468667
5	0.303194	0.309839	0.006645	-0.631451	0.527746
6	0.338502	0.317757	0.020744	0.848156	0.396351
7	0.331816	0.333723	0.001907	-1.128665	0.259039
8	0.311275	0.330586	0.019311	0.697709	0.485359
9	0.340596	0.320662	0.019934	0.763109	0.445398

With the exception of the Lusaka stock market which reported a slightly relative

TABLE 6.19: Summary Prediction Results for Nigerian Stock Exchange- LSTM

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.691045	0.697317	0.006271	0.690926	0.489612
1	0.687189	0.695873	0.008685	1.426645	0.153682
2	0.691797	0.695092	0.003294	-0.216704	0.828439
3	0.699204	0.698303	0.000901	-0.94625	0.344021
4	0.702435	0.706148	0.003713	-0.089185	0.928935
5	0.695274	0.703584	0.00831	1.312315	0.189414
6	0.719667	0.710665	0.009003	1.52358	0.127614
7	0.718899	0.718201	0.000697	-1.008484	0.313222
8	0.727736	0.727106	0.00063	-1.02883	0.30356
9	0.730798	0.732498	0.0017	-0.702796	0.482183

TABLE 6.20: Summary Prediction Results for Johannesburg Stock Exchange- BRNN

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.774963	0.006564	-0.704478	0.481135	
1	0.763355	0.756716	0.006639	-0.697919	0.485228
2	0.789477	0.758103	0.031374	1.469058	0.141817
3	0.736891	0.75258	0.015689	0.09492	0.924378
4	0.76322	0.742243	0.020977	0.558225	0.576691
5	0.755957	0.740152	0.015805	0.105119	0.916281
6	0.766222	0.732773	0.033449	1.650834	0.098772
7	0.785203	0.769886	0.015316	0.062291	0.950331
8	0.800838	0.789684	0.011154	-0.302404	0.762344
9	7 0.785413	0.793538	0.008125	-0.567759	0.570199

TABLE 6.21: Summary Prediction Results for Tunisia Stock Exchange- LSTM

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.63982	0.645792	0.005971	-0.745778	0.455801
1	0.637301	0.647063	0.009762	-0.484894	0.627751
2	0.627928	0.62296	0.004968	-0.81485	0.415158
3	0.598319	0.630597	0.032277	1.06451	0.287098
4	0.612649	0.604661	0.007988	-0.606998	0.543852
5	0.606233	0.618169	0.011936	-0.335283	0.737411
6	0.603879	0.608903	0.005024	-0.810936	0.417402
7	0.60653	0.607488	0.000958	-1.090791	0.275365
8	0.601322	0.610326	0.009005	-0.53703	0.591247
9	0.5863	0.6013	0.015	-0.124442	0.900965

high error variance, the other nine stock markets as shown in Tables 6.14-6.23 had

TABLE 6.22: Summary Prediction Results for Lusaka Stock Exchange-LSTM

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.54234	0.395684	0.146656	0.413961	0.678902
1	0.538033	0.395684	0.142349	0.331975	0.739908
2	0.544593	0.395684	0.148908	0.45684	0.647786
3	0.540166	0.395684	0.144482	0.372576	0.709464
4	0.530335	0.395684	0.13465	0.18544	0.852884
5	0.52343	0.395684	0.127746	0.054014	0.956924
6	0.514373	0.395684	0.118689	-0.11839	0.905758
7	0.513696	0.395684	0.118011	-0.131287	0.895549
8	0.512976	0.395684	0.117291	-0.144993	0.884717
9	0.511496	0.395684	0.115812	-0.173157	0.862528

TABLE 6.23: Summary Prediction Results for Zimbabwe Stock Exchange- RNN

iteration	Y	Yhat	Diff	Zscore	Pvalue
0	0.214276	0.210072	0.004204	0.790378	0.429307
1	0.219154	0.214865	0.004289	0.829754	0.406678
2	0.221378	0.218934	0.002443	-0.024004	0.980849
3	0.218859	0.222738	0.003879	0.640308	0.521972
4	0.220584	0.224008	0.003424	0.429824	0.667324
5	0.216613	0.223655	0.007042	2.103606	0.035413
6	0.213936	0.219810	0.005875	1.563457	0.117945
7	0.207310	0.215534	0.008223	2.650078	0.008047
8	0.202500	0.207588	0.005088	1.199336	0.230397
9	0.205155	0.199978	0.005177	1.240667	0.214729

minimal variance between the predicted and the actual figures.

Figure 6.1 reveals the relationship between the z-score and p-values. Considering =0.05, the null hypothesis is accepted when the z-scores are between -1.96 and 1.96. If values are above this range, then null hypothesis is rejected. The hypothesis for this research is as follows;

H0: There is no difference between the actual and predicted values

Ha: There is a difference between the actual and predicted values

A close survey of the sample values shows that at =0.05, the values overally are in the acceptance region between -1.96 and 1.96. Therefore, the research results show that the null hypothesis is accepted. If p-values >0.05, we fail to reject the null hypothesis as exemplified in the results above.

6.3 Performance of GAM in Predicting Stock Market Price Index

Table 6.24 below shows that GAM was able to predict stock price indices for the 10 African stock markets. The lowest prediction accuracy was for Egypt with 97.55%

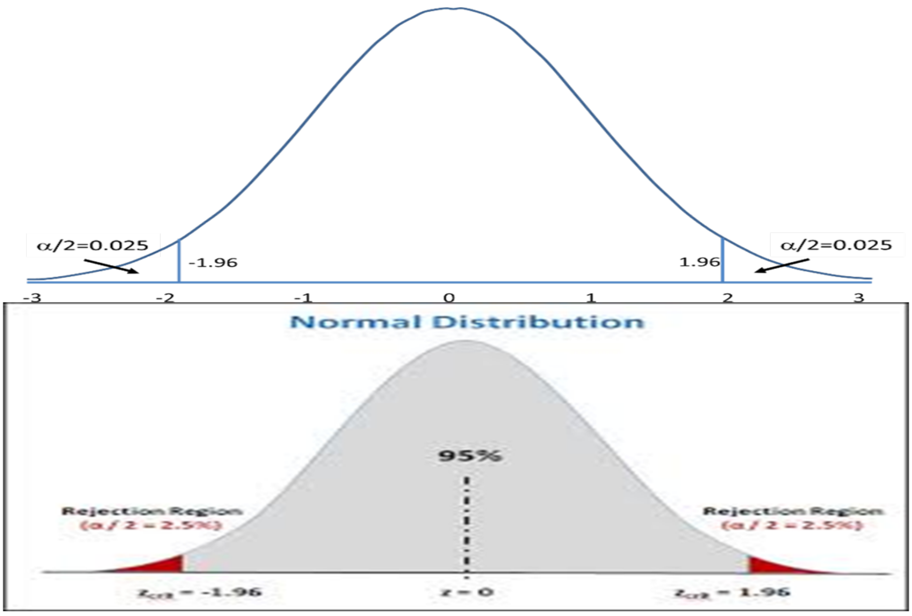

FIGURE 6.1: Critical Regions

whilst the highest was for the Namibian bourse with 100.00% prediction accuracy. The null hypothesis for the experiments was that there is no difference between the actual and predicted values. Results are rejecting the alternate hypothesis and accepting the null hypothesis for all countries except for Morocco, Zimbabwe and S&P500 whose zscores are above ±1.96.

GAM results also point to prediction of the upper and lower forecast closing prices for the next day as shown in Table 6.25. The GAM forecast results are reported in three forecast bandwidths namely predicted closing price, upper predicted closing price and lower predicted closing price. The upper and lower predicted prices are linked to the notion of resistance and support levels and can be used to formulate trading strategies. If prices cross the upper predicted price, it is considered a sell signal and if prices crosses the lower predicted price, it is considered a buy signal. This strategy is called a contrarian strategy whereby the upper price is used as resistance in an upward trend and the lower price is used as support in a downtrend. Therefore, GAM prediction results can be used by traders to formulate trading strategies .

6.3.1 Graphical Representation of Botswana Prediction Results

Fig 6.2 below is a graphical representation of a year ahead forecast for Botswana Stock Exchange. The model's ability to forecast a year ahead clearly outlines the application of statistical networks to prediction of African stock markets. The blue band represents the predicted variables and the black dots represent actual variables.As observed from the results, GAM models do not only predict absolute values but also point to directional change in the market. It is observed from Fig 6.2 below that a visual presentation of stock market volatility is noticeable and guides investment and trading policies.

TABLE 6.24: Sample of Empirical Results for GAM Predictions

Country	Date	Actual price	Forecast price	Accuracy	Pvalue	Zscore
Botswana	0	6.832369	6.863061	99.76	0.9463	1.610
-	1	6.829388	6.862539			
-	2	6.829917	6.855821			
Egypt	0	4.871717	5.135923	97.55	0.7349	0.6276
-	1	4.862623	5.148055			
-	2	4.862889	5.144487			
Kenya	0	-0.251736	-0.275153	100.00	0.3249	0.4538
-	1	-0.241855	-0.238294			
-	2	-0.239006	-0.173804			
Mauritius	0	4.163405	4.115217	99.21	0.0389	1.7637
-	1	4.167569	4.123147			
-	2	4.158637	4.112701			
Morocco	0	7.166496	7.203672	99.50	0.0161	2.1419
-	1	7.151629	7.161336			
-	2	7.14211	7.134551			
Nigeria	0	4.860511	4.878546	99.32	0.8671	1.1129
-	1	4.861386	4.882607			
-	2	4.851206	4.89401			
South Africa	0	8.30551	8.40951	99.58	0.2564	0.6545
-	1	8.291276	8.40003			
-	2	8.297291	8.38744			
Tunisia	0	8.059879	8.047616	99.88	0.7869	0.7957
-	1	8.049797	8.080291			
-	2	8.04301	8.033548			
Zambia	0	6.651844	6.574812	99.59	0.7311	0.6162
-	1	6.640492	6.583186			
-	2	6.641643	6.600482			
Zimbabwe	0	4.963404	4.937888	99.52	0.0135	2.2103
-	1	4.941928	4.922055			
-	2	4.940928	4.986051			
S&P500	0	7.194512	7.152316	99.57	0.0010	3.0796
-	1	7.213467	7.152504			
-	2	7.237342	7.15443			

TABLE 6.25: Sample of Botswana GAM Prediction Results for Contrarian Strategies

Date	Actual Closing Price	Forecast price	Forecast price Lower	Forecast price Upper
04/01/2017	6.780981323	6.750906	6.701526	6.798362
05/01/2017	6.780871922	6.750123	6.700834	6.80123
06/01/2017	6.780740254	6.749937	6.702808	6.7968
09/01/2017	6.783386762	6.745072	6.696791	6.795516
10/01/2017	6.782682061	6.745127	6.696601	6.795392
11/01/2017	6.778469387	6.742818	6.698525	6.790606
12/01/2017	6.787765746	6.742111	6.690991	6.796032

6.3.2 Seasonal Components of the Forecast Time Series for Botswana Stock Exchange

The GAM model also was able to decompose time series into yearly, weekly, daily and holiday trends. The overall trend is forecasting a downward trend for the bourse post 2015. Yearly decomposed trends reveal that the Botswana Stock Exchange is at its lowest levels in January and the market picks generally over the entire trading year with the highest peak in April. The results are in contrast to the January effect where market prices are believed to be high and provide the best returns in January. This shows the uniqueness of African stock markets. Different country specific influencing factors can be the cause for this phenomenon. However, the Botswana stock exchange was not spared from the effects of the 2016 China stock market crash and the US Presidential elections in 2016, where a slump in market performance is

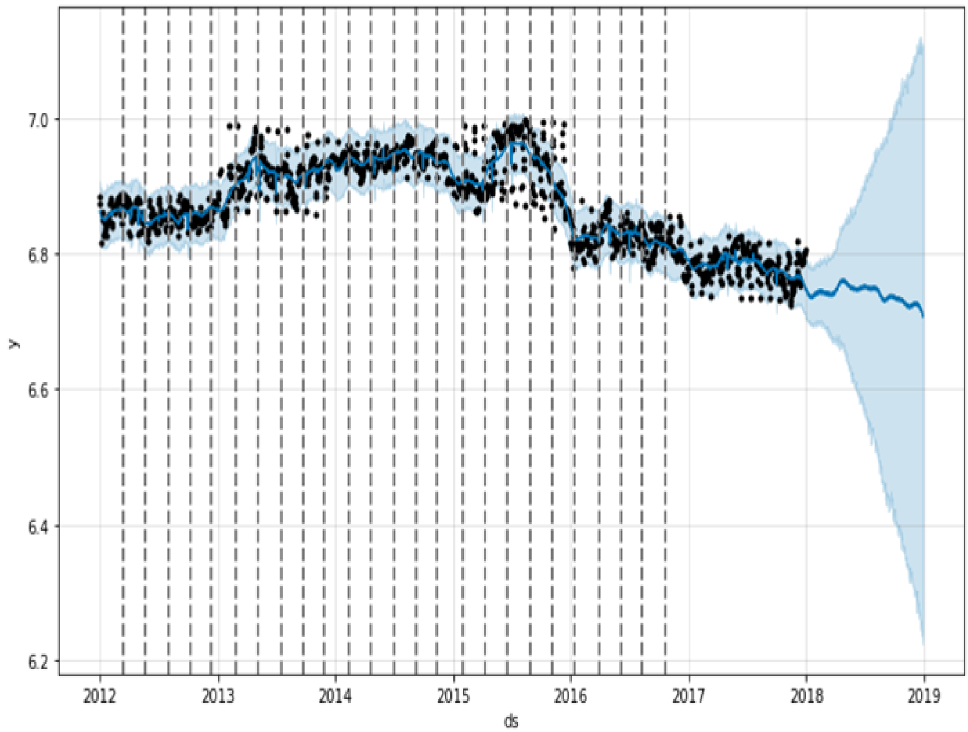

FIGURE 6.2: Graphical Representation of GAM Results for Botswana Stock Exchange

noted.

6.4 Prediction Results for Egypt

It can be noted in Figure 6.4 that major shocks hit the Egyptian stock market in the period 2012-2014. The market self adjusted from 2014 onwards but with a further slump in the period 2016 right into the forecast period.

Graphical Representation of Egypt Stock Exchange Results

6.4.1 Seasonal Components of the Forecast Time Series for Egypt Stock Exchange

The time series decomposition for the Egyptian bourse in figure 6.4 explicitly reveals that a downward trend is expected post 2017. Weekly trends reveal that the stock market is at its highest and best return platform on a Tuesday and it is lowest on a Friday. Figure 6.5 also shows that the month of October is the best time to go short and in January is the best time to go long. Results are pointing to October as the month of best returns. January posted very low returns and the January effect is not present for the Egyptian stock exchange.

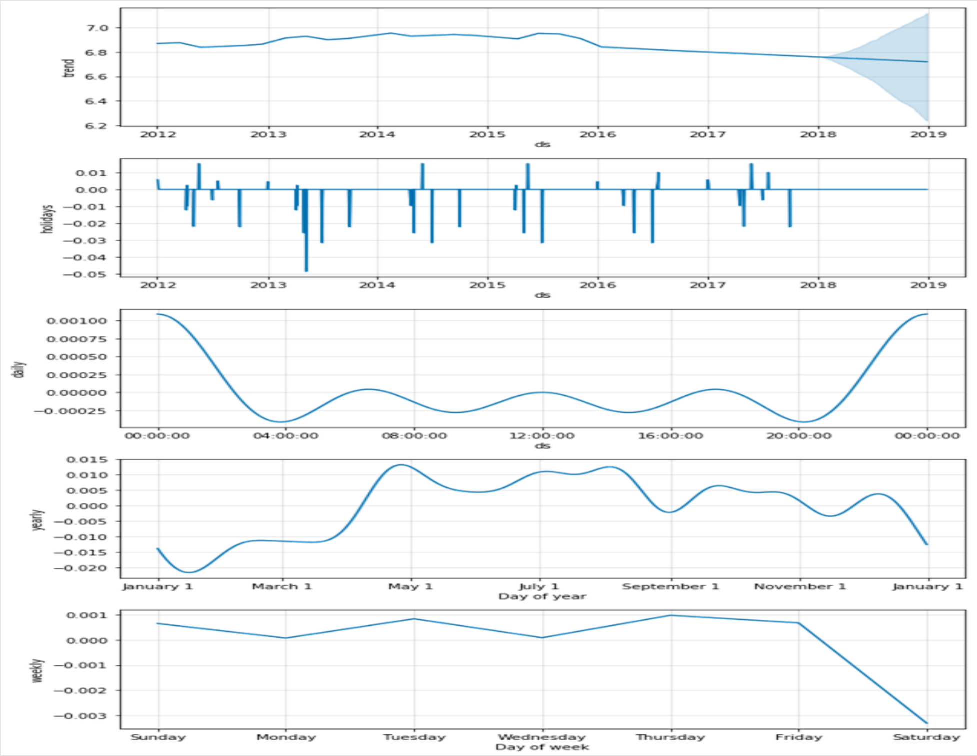

FIGURE 6.3: Seasonal Components of the Time Series for Botswana Stock Exchange

6.5 Prediction Results for Mauritius

6.5.1 Graphical Representation of Mauritius Prediction Results

The Stock Exchange of Mauritius experienced major market shocks in the period 2012 to 2013 as well as 2015-2016. It is expected to increase in the forecasting period with periodic upswings and downswing movements. No major shocks in the market are expected in the forecasting period.

6.5.2 Seasonal Components of the Forecast Time Series for the Stock Exchange of Mauritius

The time series decomposition for the Mauritian bourse explicitly reveals that an increasing trend is expected into the forecast period. Weekly trends reveal that the stock market is at its highest and best return platform on a Tuesday and it is lowest on a Wednesday. Figure 6.6 also shows that the month of May is the best time to go short and November is the best time to go long.

6.6 Prediction Results for Morocco

6.6.1 Graphical Representation of Morocco Prediction Results

Even though the market started declining in 2012 to about 2013, it reverted back on an upward trend in 2014. Another downward movement was noticeable in 2015. However, towards the end of 2015, the market had a downtrend which will project

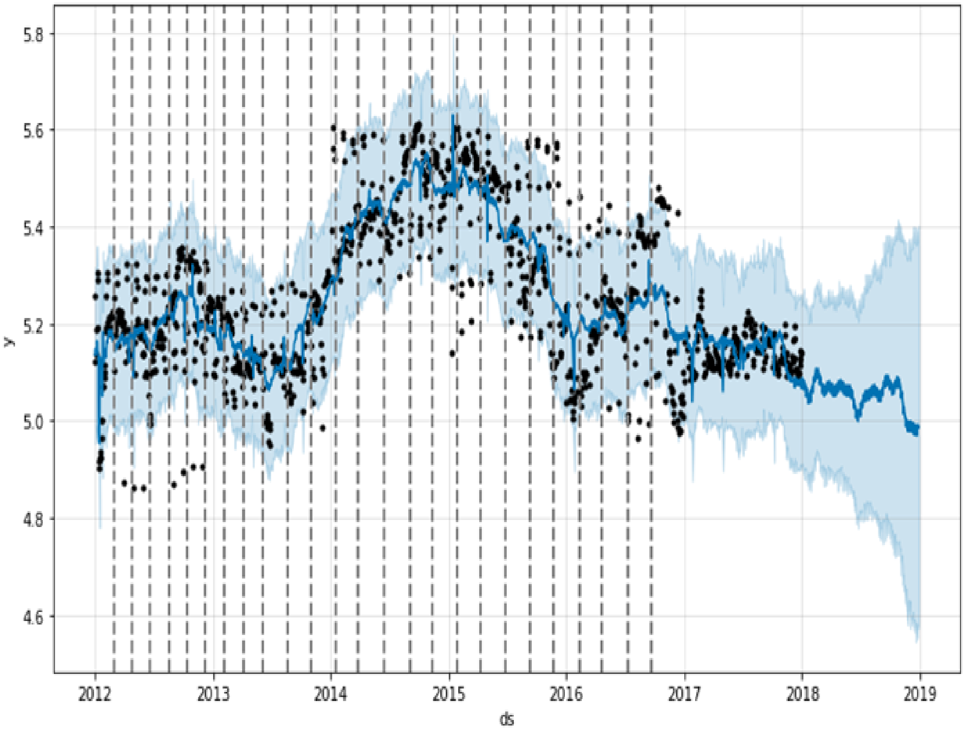

FIGURE 6.4: Graphical Representation of GAM Results for Egypt Stock Exchange

into the 2016 period. The period post 2016 is expected to be bullish according to these results.

From a policy perceptive, circuit breakers in the major downfall in 2011 to 2013 are very essential in order to avoid panic selling and buying on either upswing direction and avoid market crashes. However, stock market regulators should really consider the pros and cons of circuit breaking rules upon implementation. Possible advantages include price stabilization effect, cooling off effect and wealth effect while disadvantages may encompass price overflow effect, delayed price discovery effect, trading interference effect and magnet effect.

6.6.2 Seasonal Components of the Forecast Time Series for the Stock Exchange of Morocco

The time series decomposition for the Moroccan bourse explicitly reveals an upward trend post 2017. Weekly trends reveal that the stock market has highest peak on Tuesday and it is lowest on a Wednesday. Figure 6.8 also shows that the month of February is the best time to go short and October is the best time to go long. The best returns are achieved in February though the month of January showed increasing return capability.

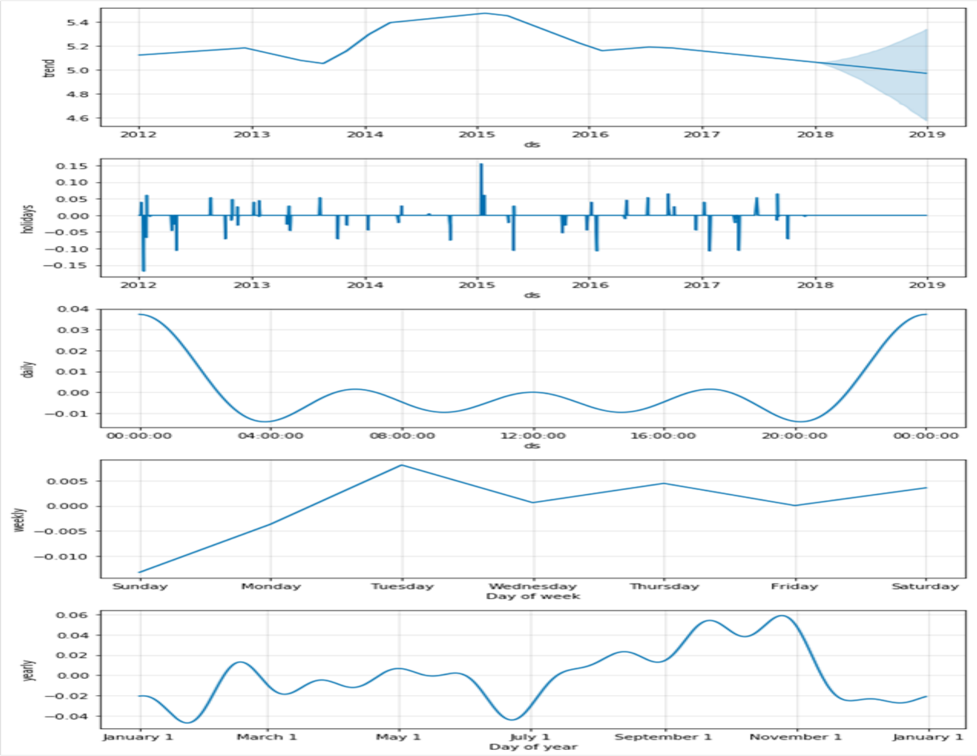

FIGURE 6.5: Seasonal Components of the Time series for Egypt Stock Exchange

6.7 Prediction Results for Nigeria

6.7.1 Graphical Representation of Nigeria Prediction Results

The Nigerian Stock Exchange took an upswing in 2012 followed by a downward swing from 2014 to 2017. As we move into the forecast period in 2017/2018, the Nigerian Stock Exchange is expected to be on an increasing trend.

6.7.2 Seasonal Components of the Forecast Time Series for Nigeria Stock Exchange

The time series decomposition for the Nigerian bourse explicitly reveals a declining trend which is expected to go up post 2017. Weekly trends reveal that the stock market has the highest returns on Wednesday and lowest returns on a Monday. Figure 6.10 also shows that the month of October is the best time to go short and February is the best time to go long.

6.8 Prediction Results for South Africa

6.8.1 Graphical Representation of South Africa Prediction Results

Figure 6.12 reveals a fairly stable market over time. However, the market exhibits a decline from 2015 into 2016. It then self corrects to have an upward trend post 2016 with a sharp rise or positive market direction. This exhibits that stock markets mean revert. The economic recession in South Africa in 2016 caused the markets to slump

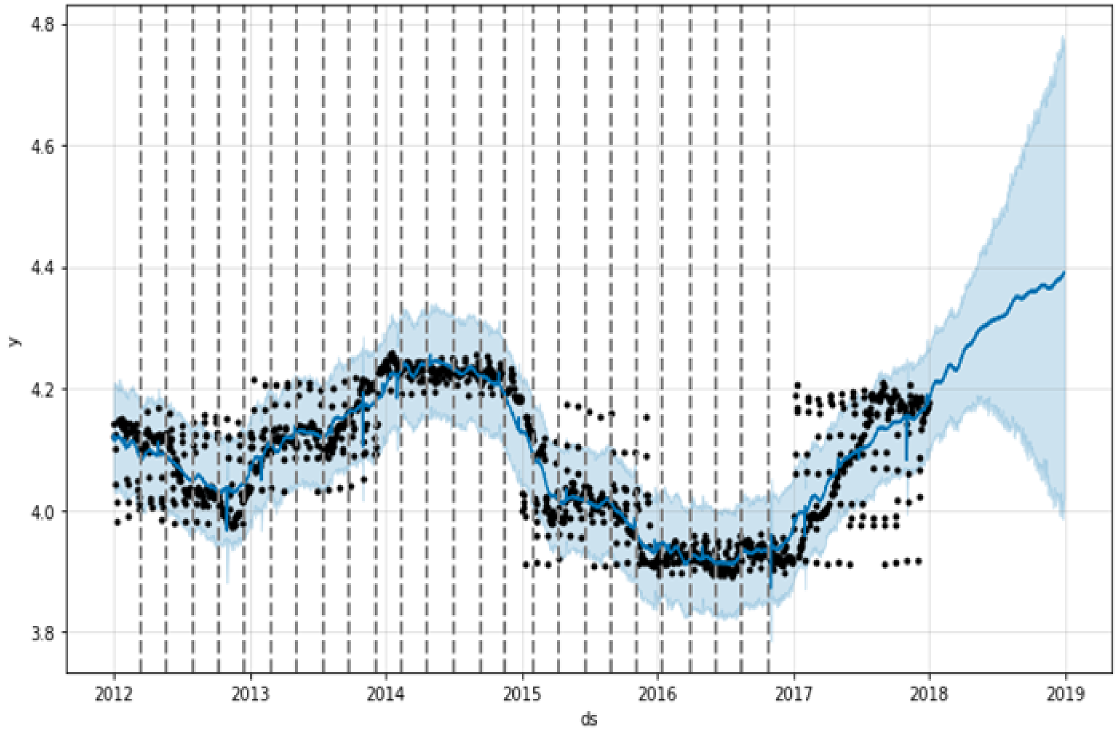

FIGURE 6.6: Graphical Representation of GAM Results for Stock Exchange of Mauritius

down aggressively. The possibility of spill overs from Nigeria and South Africa as Africa's two biggest economies could have induced the low performance in all the other African markets in 2016. This is in addition to impact of global events such as the 2016 China stock market crush on African stock markets.

6.8.2 Seasonal Components of the Forecast Time Series for Johannesburg Stock Exchange

The time series decomposition for the Johannesburg bourse explicitly reveals that an upward trend is expected into the forecast period. Weekly trends reveal that the stock market has the highest returns on Tuesday and lowest returns on a Wednesday. Figure 6.13 also shows that the month of May is the best time to go short and in January is the best time to go long.

6.9 Prediction Results for Tunisia

6.9.1 Graphical Representation of Tunisia Prediction Results

Ever since the downward market swing which commenced in 2012, the Tunisian stock exchange trajectory is set on a downward trend into the forecast period. The highest return period in 2012 is followed by a declining trend as exhibited in figure 6.14.

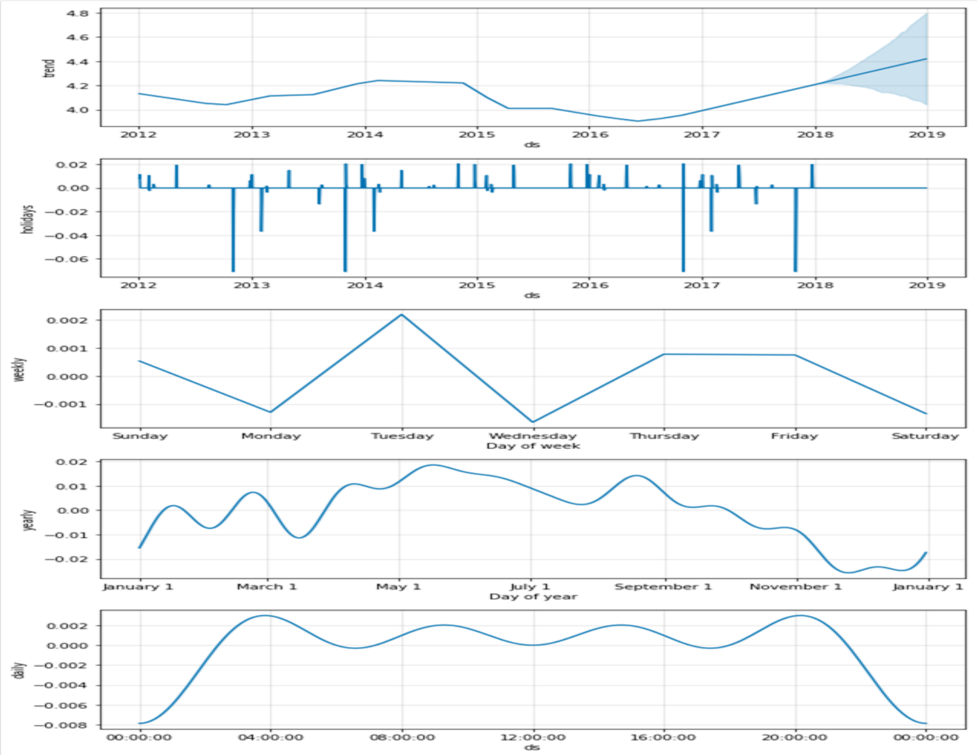

FIGURE 6.7: Seasonal Components of the Time Series for Stock Exchange of Mauritius

6.9.2 Seasonal Components of the Forecast Time Series for Tunisian Stock Exchange

The time series decomposition for the Tunisian bourse explicitly reveals that a downward trend is expected into the forecast period. Weekly trends as exhibited in figure 6.15 reveal that the stock market has the highest returns on Friday and lowest returns on a Thursday. Figure 6.15 also shows that the month of August is the best time to go short and in January is the best time to go long.

6.10 Prediction Results for Zimbabwe

6.10.1 Graphical Representation of Zimbabwe Prediction Results

The trajectory for the Zimbabwean bourse is set to increase post 2017, after a slump in 2016. The slump is attributable to effects of currency reforms and China stock market crash. Zimbabwe relies heavily on mineral exports and where greatly affected when the commodities market took a recession in 2016.

6.10.2 Seasonal Components of the Forecast Time Series for Zimbabwe Stock Exchange

The time series decomposition for the Zimbabwean bourse explicitly reveals that an upward trend is expected into the forecast period. Weekly and monthly trends as exhibited in figure 6.17 reveal that the stock market has the highest returns on Friday

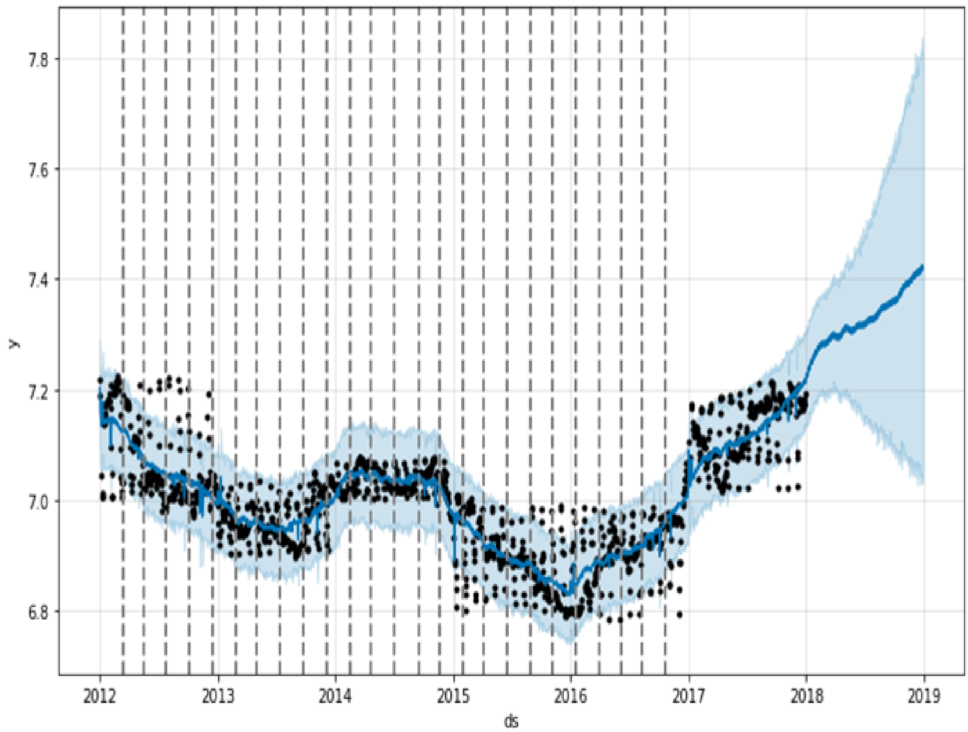

FIGURE 6.8: Graphical Representation of GAM Results for Morocco Stock Exchange

and lowest returns on a Thursday whilst monthly trends show that the month of October is the best time to go short and in August is the best time to go long.

6.11 Prediction Results for Zambia

6.11.1 Graphical Representation of Zambian Prediction Results

The Zambian bourse is forecast to be bullish post 2017. Ever since the market started to decline towards the end of 2014, it is still expected to go down intensively until 2017 and take on an upward trend.

6.11.2 Seasonal Components of the Forecast Time Series for Lusaka Stock Exchange

The time series decomposition for the Zambian bourse explicitly reveals weekly and monthly trends as exhibited in figure 6.19 and shows that the stock market has the highest returns on Tuesday and lowest returns on a Thursday, whilst monthly trends show that the month of August is the best time to go short and in February is the best time to go long.

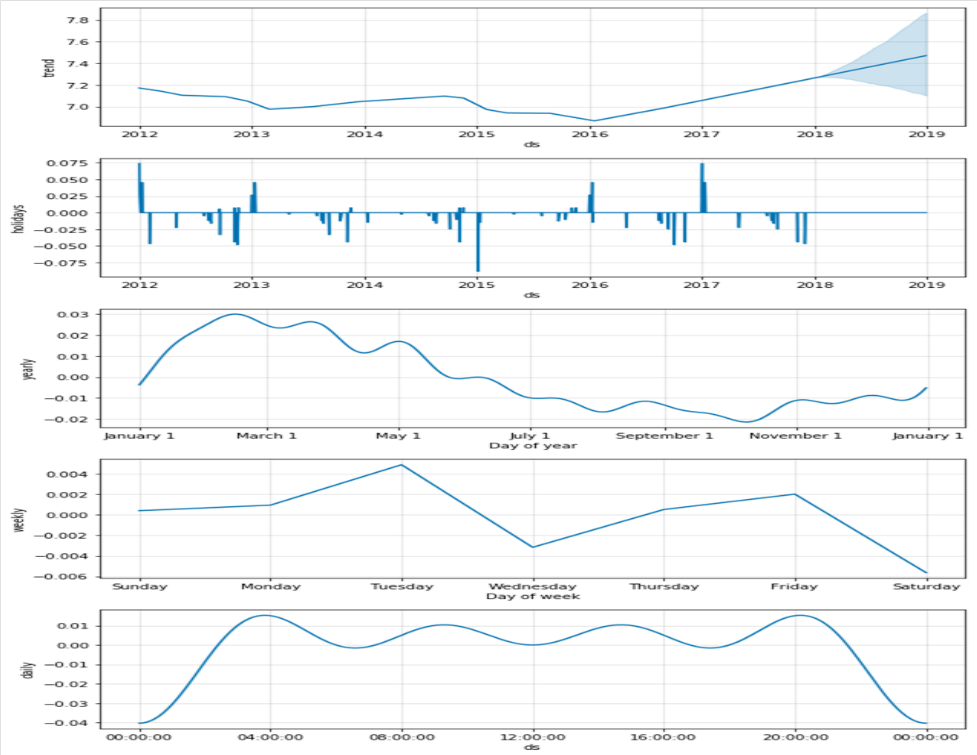

FIGURE 6.9: Seasonal Components of the Time Series for Morocco Stock Exchange

6.12 Prediction Results for Kenya

6.12.1 Graphical Representation of Kenya Prediction Results

The Kenyan bourse is forecast to be bullish in the forecast period, but with some ups and downs. Ever since the market started to decline in 2015, it is still expected to go down until 2017 where its forecast to start going up, but with up and down movements.

6.12.2 Seasonal Components of the Forecast Time Series for Nairobi Stock Exchange

The time series decomposition for Nairobi bourse explicitly reveals that an upward trend is expected into the forecast period. Weekly and monthly trends as exhibited in figure 6.21 reveal that the stock market has the highest returns on Wednesday and lowest returns on a Monday whilst monthly trends show that the month of April is the best time to go short and in December is the best time to go long.

6.13 Prediction Results for S&P 500

6.13.1 Graphical Representation of S&P 500 Prediction Results

The S&P500 is set to have an increasing trajectory post 2017. However, a slight drop was incurred around 2016 as was experienced in all other stock markets under consideration in this research. All the selected African markets reacted to the

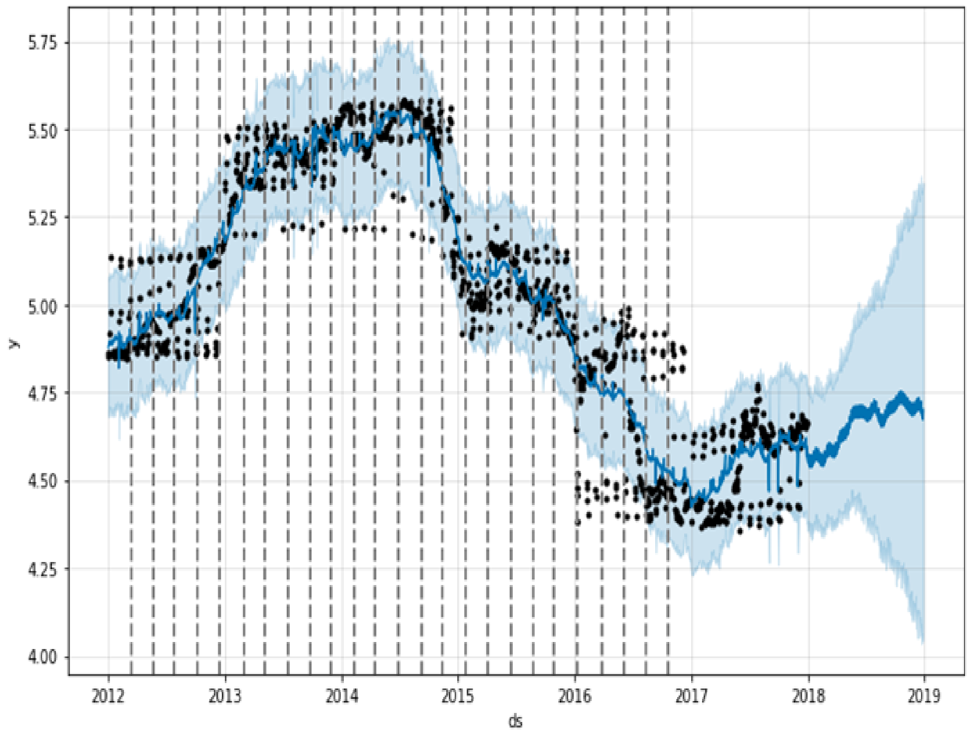

FIGURE 6.10: Graphical Representation of GAM Results for Nigeria Stock Exchange

China Crash of 2016 and US Presidential Elections. This suggests that the selected African countries stock movements are influenced by stock movements in the USA and China.

6.13.2 Seasonal Components of the Forecast Time Series for S& P500

The time series decomposition for S& P500 explicitly reveals that an upward trend is expected into the forecast period. Weekly and monthly trends as exhibited in figure 6.23 reveal that the stock market has the highest returns on Tuesday and lowest returns on a Monday whilst monthly trends show that the month of January is the best time to go short and in December is the best time to go long.

6.14 Prediction Summary on GAM

This section presents summarized calendar effects (Day of the Week effect, Month of the Year effects and Halloween Effects) for the countries under consideration. Herewith in Table 6.6 below is a summary of the day of the week and month of the year effects.

Calendar effects vary amongst countries owing to differing capital market characteristics (Diaconasu et al., 2012). This was noted in the research findings of this study. To start with, evidence of the January effect was only found for the S&P500 where returns are generally higher in January and lower in December. This is in agreement with studies by (Plastun et al., 2020) who cite that the January effect still remains established in the US market. However, their study did not recognise any

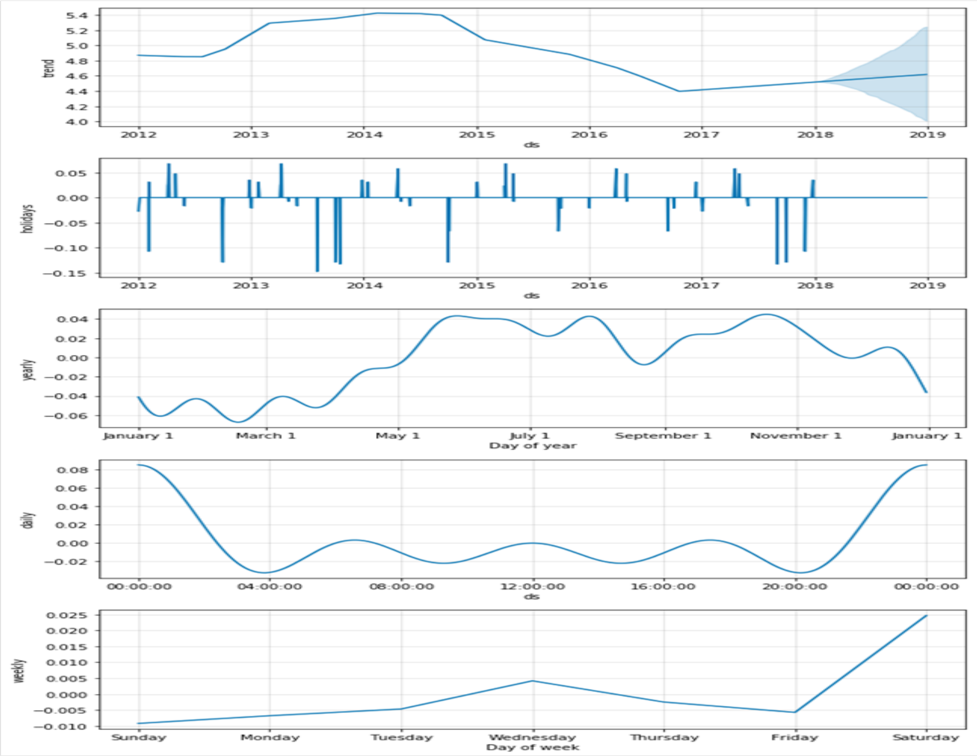

FIGURE 6.11: Seasonal Components of the Time Series for Nigeria Stock Exchange

TABLE 6.26: Summary of Weekly and Monthly Highs and Lows

Country	Weekly Lowest	Weekly Highest	Monthly Lowest	Monthly Highest
Botswana	Monday	Thursday	January	April
Egypt	Friday	Tuesday	January	October
Kenya	Monday	Wednesday	December	April
Mauritius	Wednesday	Tuesday	November	May
Morocco	Wednesday	Tuesday	October	February
Nigeria	Monday	Wednesday	February	October
South Africa	Wednesday	Tuesday	January	May
Tunisia	Thursday	Friday	January	August
Zambia	Thursday	Tuesday	February	August
Zimbabwe	Thursday	Friday	August	October
SP500	Monday	Tuesday	December	January

December effect which is in contrast to this research finding. A possible explanation of this January and December effects is either the tax loss selling hypothesis or window dressing hypothesis.

Under tax loss selling hypothesis, investors sell of their stocks in December and buy them back in January causing an increased demand for stock, and in turn prices go up. The window dressing hypothesis is when investors dispose their stocks at year end in pursuit of presenting a more acceptable portfolio performance in year end reports. Thus, in this research, January returns for the S& P500 are attainable and significantly higher than the other months of the year. The tax year for the US ends in December and possibly could be a contributing factor to the low December returns and high January returns. In other words, the tax low hypothesis is most

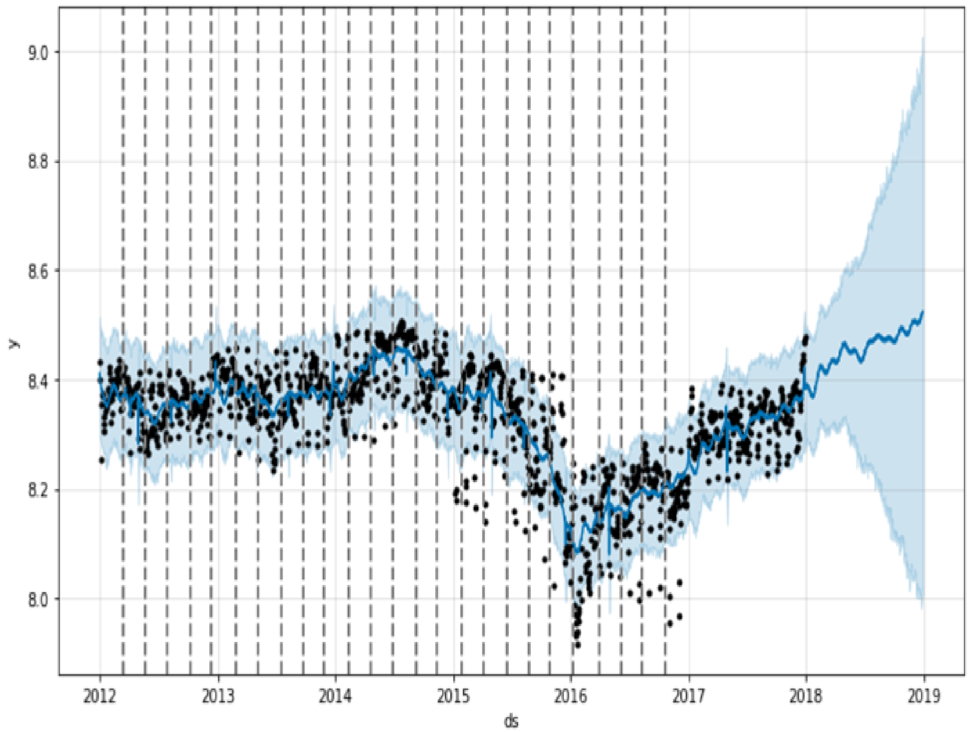

FIGURE 6.12: Graphical Representation of GAM Results for Johannesburg Stock Exchange

ideal to explain this study's findings on the S& P500.

Interestingly, results from this study point to the fact of the non-existence of January effect in most African stock markets despite the fact that most of their tax years ends are in December. For Botswana, Egypt, South Africa and Tunisia, low returns are noted in January whilst evidence of low February returns is noted in for Nigeria and Zambia. This in contrast to the January effect were returns are expected to be significantly high in January. This research finding points to the fact that monthly effects are noticeable in other months other than January. This is in agreement with (Girardin and Liu, 2014) who identified that it was not possible to detect month-of-the-year effects in returns for Zimbabwe and other countries.

However, the best returns are noted in April, May, August and October[1] for most countries under consideration in this research. This suggests existence of April Effect, May effect, August effect and October effect. It can be suggested that since some of the African countries allow tax submission three months after year end, individuals and corporations can dispose their stocks in March, hence lowering the prices. However, in April, they buy back, causing an increased demand for shares and cause share price increases. Hence, the tax loss hypothesis can apply for submissions done in March. In addition, the research findings concur with (Norvaisiene et al., 2015) findings in developing or small markets. They found evidence of seasonality but the seasonal fluctuations of stock prices in these countries were evidenced not only in January, but in any other month of the year.

In addition, research finding on the week effect reveal that the US returns are significantly negative on Mondays but significantly positive on Tuesday than on Friday

[1]Botswana, Kenya (high in April); Mauritius and South Africa(high in May); Egypt, Tunisia and Zambia(high in August); Nigeria and Zimbabwe (high in October).

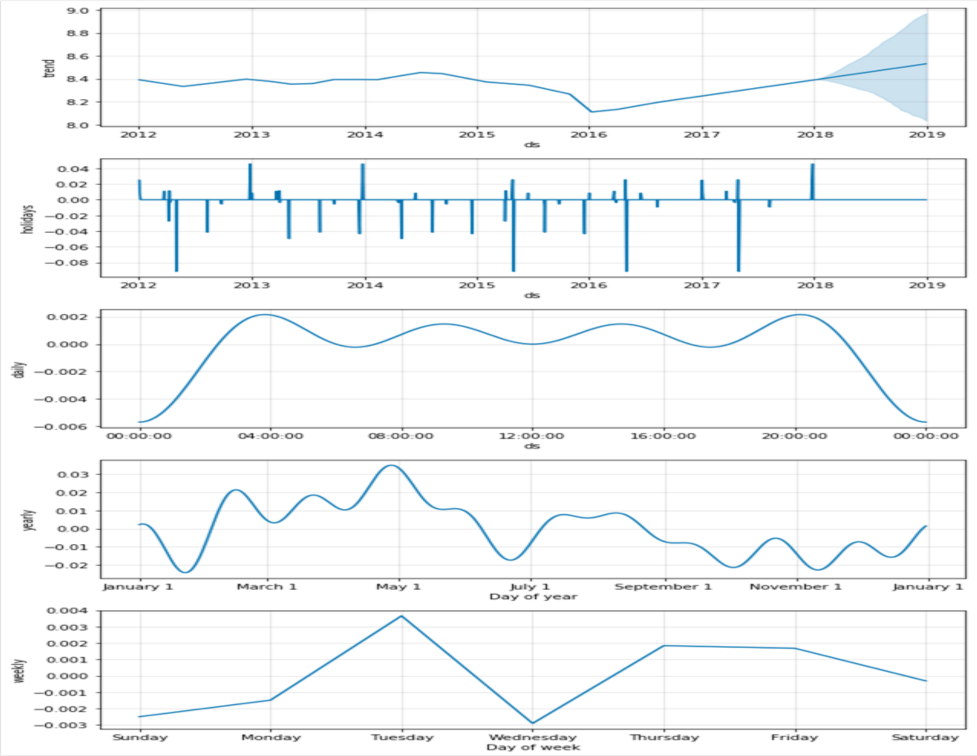

FIGURE 6.13: Seasonal Components of the Time Series for Johannesburg Stock Exchange

as postulated by (Al-Khazali et al., 2008) . A leading hypothesis for the weekend effect (Low Monday returns and High Friday returns) is the arrival of negative news at the beginning of the week (Caporale and Zakirova, 2017; Agrawal and Tandon, 1994; French, 1980) . This result findings also concur with French (1980) who also attained negative returns on Monday's for the S&P500. In addition, the low returns on Monday can also either be attributed to low trade transactions on a Monday dampening the share price or to the changing mood of investors who begin the week at a low mood and increase positive mood during the week (Plastun et al., 2019a) .

Evidence of new day of the week effect was noted for the African markets under consideration in this research. A Wednesday effect is noted for Mauritius, Morocco and South Africa with low returns on a Wednesday and high returns on a Tuesday. Similarly, Tunisia and Zimbabwe experience a Thursday effect with low returns on a Thursday and high returns on a Friday. Evidence of a Monday effect is noted for Botswana, Kenya, Nigeria and the S& P500. However, high returns in these markets are attainable on Thursday, Wednesday and Tuesday respectively. A plausible explanation for these results could be varying settlement periods in the respective countries as espoused in the settlement procedure hypothesis in agreement with (Ariss et al., 2011) .

For all the 11 countries (including the US) studied in this research, there is no evidence of the Halloween effect in 10 out of the 11 countries except for Mauritius. The Halloween effect indicates that returns between November and April are higher than in other months of the year (Plastun et al., 2019a; Norvaisiene et al., 2015). This study finding are largely in agreement with (Norvaisiene et al., 2015) finding that in small and emerging markets, there is no existence of the Halloween effect. However, a new 20th century phenomena is that shifts have been noted between the November

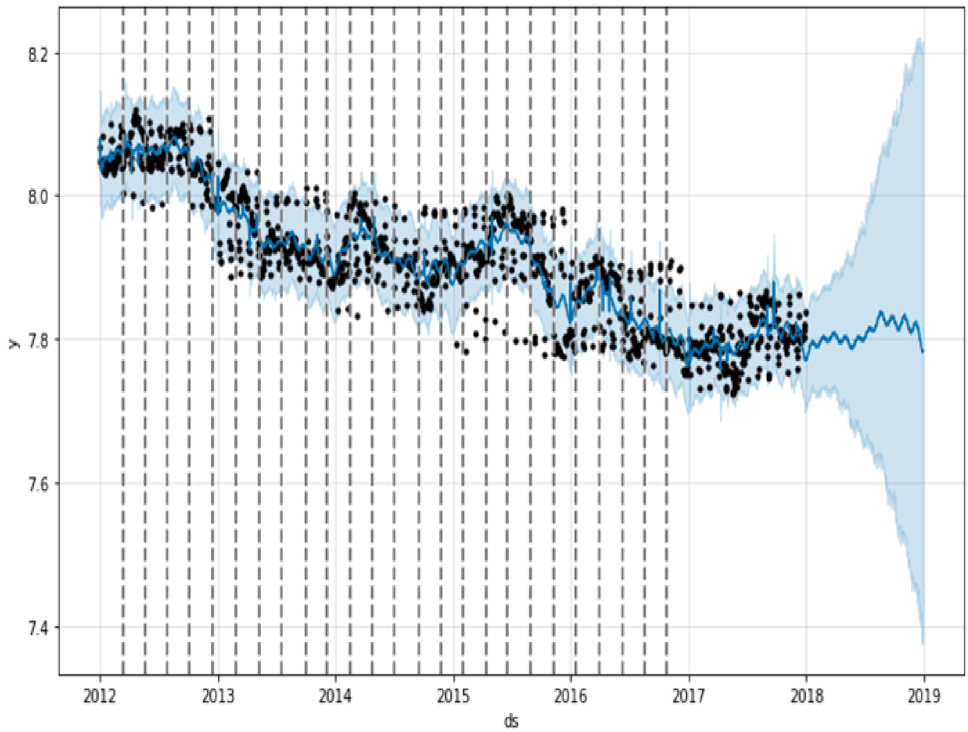

FIGURE 6.14: Graphical Representation of GAM Results for Tunisian Stock Exchange

to April months and the May to October months (Plastun et al., 2019b) . Mauritius is the only country that meets the May to October 20th century phenomena with best returns recorded between May and October. This study did not find a Halloween effect on the S& P500. In addition, negative returns were recorded for all financial markets in this study during holidays. As in (Wasiuzzaman, 2018) study, holiday effects have a negative impact on stock returns.

Another key observation from the research results is that African stock markets experienced a slump in prices during the 2016 and 2017 period. This could have been an effect of the china stock market crash of 2016, which affected global markets. Most African countries also have China as a trading partner; hence this crash affected their market too. In addition, the 2016-17 periods also noted a slump in commodity prices worldwide. Hence, all African countries that rely on commodity exports were greatly affected.

Evidence on the existence of calendar anomalies supports the view that stock markets are adaptive agents as postulated in the Adaptive market hypothesis. Owing to the fact that calendar anomalies are existent in the selected African countries, it can be concluded that these African stock markets are inefficient. Calendar anomalies vary over time making them consistent with the adaptive market hypothesis. The researcher concurs with (Zhang et al., 2017b) Zhang et al., (2017) that in addition to other stock market analysis tools, investors can exploit calendar anomalies in order to maximize their investment returns.

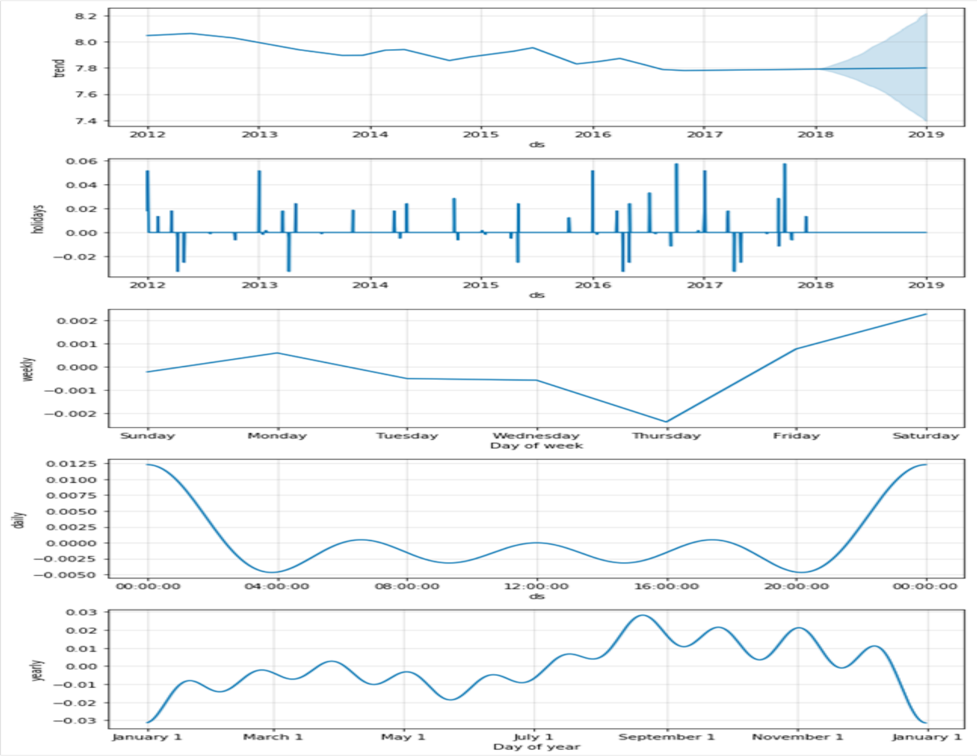

FIGURE 6.15: Seasonal Components of the Time Series for Tunisian Stock Exchange

6.15 Time Series results for sub Saharan African stock market indices

The following results were determined for time series econometric analysis after running unit root tests, cointegration and causality tests.

6.15.1 Unit root testing

Unit root tests using the ADF technique was conducted for all the stock markets under consideration in this study. lnCPI for Botswana is stationary and significant at level (5% significance) and for Mauritius lnClose is stationary and significant at level (5% significance) . For all other indices under consideration in this research, H0 was rejected for all variables indicating unit root at I (0). After first differencing, all variables contain no unit root at I (1) at the 5% level of significance as shown in Table 6.7 that follows. For a particular index in which a certain macroeconomic variable was not used due to unavailability of data, it is represented with an -.

6.15.2 Multivariate Regression Results

In order to determine which macroeconomic factors influence share price movement in stock markets, a country time series analysis was conducted. Table 6.8 below shows regression results for each index. It can be deduced that the macroeconomic variables used in this research were able to influence stock price movements mostly at 1% significance level. Weaker relations were noted for Tunisia, Botswana and Zimbabwe with R^2 of 15.2%, 48.8% and 18.2% respectively. The highest R^2 is for

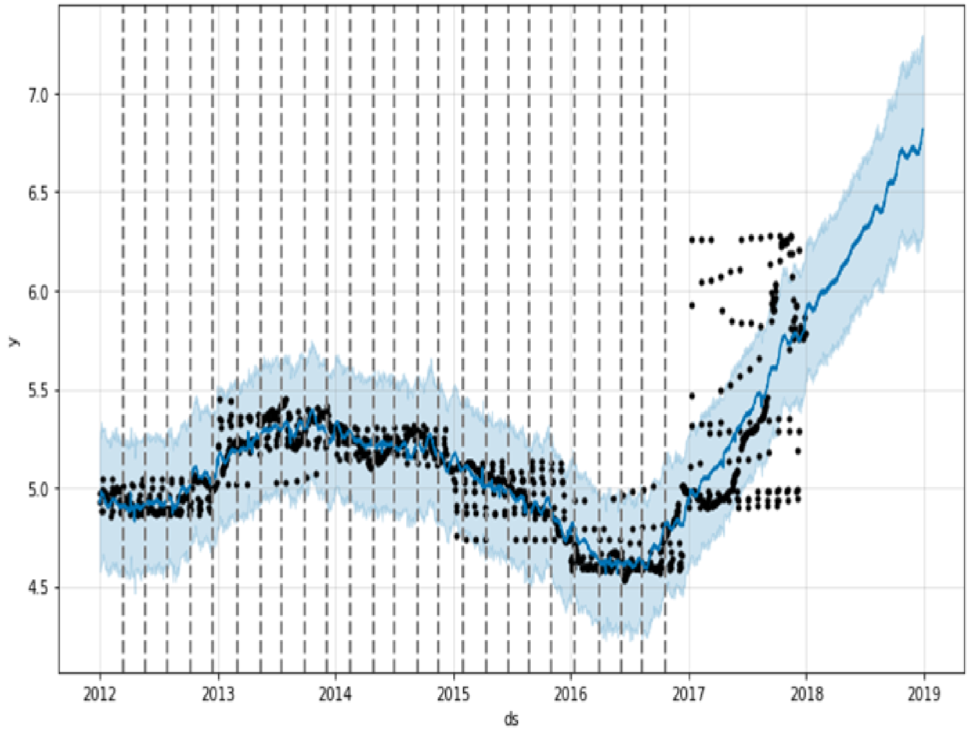

FIGURE 6.16: Graphical Representation of GAM Results for Zimbabwe Stock Exchange

South Africa at 94.3%. This implies that the variation in the Johannesburg stock market is explained by the macroeconomic variables included in this study.

The following table exhibits how each macroeconomic variable is related to closing price and is compared to previous studies in Table 6.10.

The result for Botswana shows a 48.8% significant variation in closing price to macroeconomic variables and is explained by the following equations;

$$lnclose = 7.327 + 0.676lnm2 - 0.515lnexr - 1.257lncpi - 0.286lnint$$

Money supply, exchange rate, inflation and interest rates have a positive, negative, negative and negative long run equilibrium relationship respectively with Botswana stock closing price index based on the error correction model. The coefficient of error correction term (ECT) is negative (-0.0696) and significant implying that the closing stock price is correcting its previous period's level of disequilibrium at a rate of 6.96 percent per month. There is a short run causality of its own lag on closing price but no short run causality on closing price derived from inflation, money supply, interest rate and exchange rate. A single cointegration equation (k=1) was found for the Botswana stock index. The granger causality results are showing a bidirectional causality between closing price to inflation and exchange rate and a unidirectional causality from closing price to interest rate was also determined.

A significant variation of 75.2% in closing price to economic variables was noted for the Egyptian bourse. The OLS relationship is explained as follows;

$$lnclose = -39.94 + 5.592lnm2 - 2.210lnexr - 5.473lncpi - 1.056lnint$$

Two cointegration equations are reported for this bourse with the k=1 reflecting a long run equilibrium relationship of the stock index to macroeconomic variables.

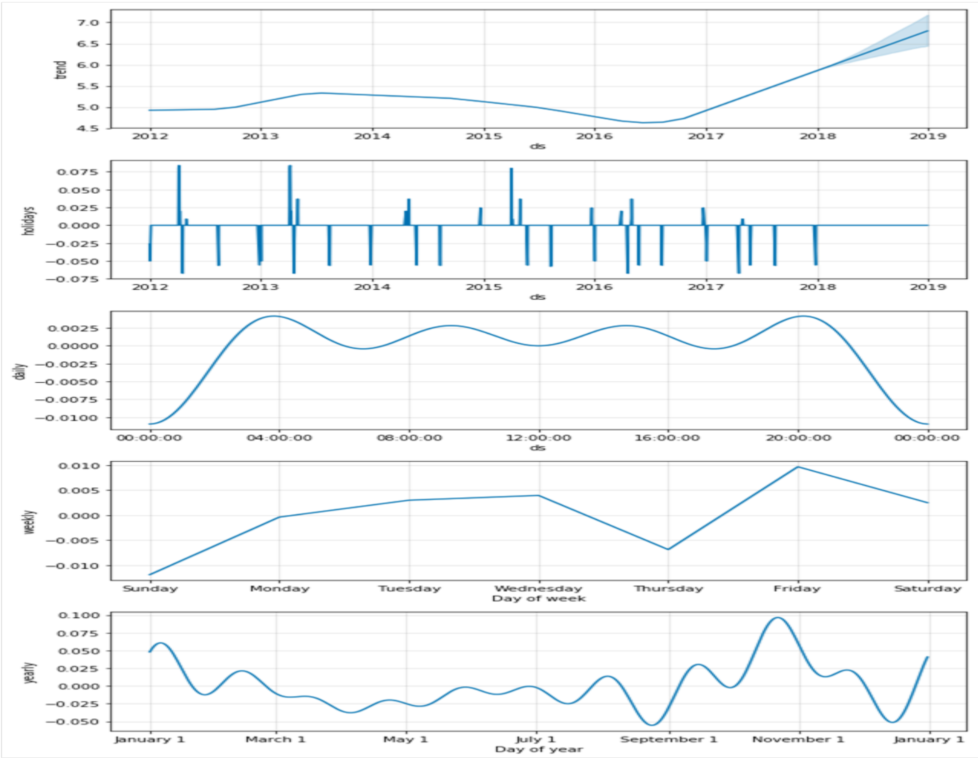

FIGURE 6.17: Seasonal Components of the Time Series for Zimbabwe Stock Exchange

However, this first equation is not significant and is correcting its previous period's level of disequilibrium at a rate of 0.75% per month, implying that the macroeconomic factors had no significant effect on closing price. This is seconded by the second (k=2) equation which exhibits no long run equilibrium relationship. In addition, no significant short run relationships between closing price and macroeconomic variables are noticeable. According to the Granger causality results, a unidirectional causality from interest rate to closing price was noticeable and that all the four macroeconomic variables combined are able to Granger cause closing price. According to the OLS results, money supply is positively related to closing price whilst all the other variables are negatively related to closing price. In reference to (Barakat et al., 2016) study, the aforementioned results are similar on the relationship between closing price and money supply but different for all other associations.

With regards to the Kenyan bourse, a cointegration equation (k=1) was determined for the bourse exhibiting a positive, negative, negative and positive associations for money supply, inflation, exchange rate and interest rates respectively with closing price respectively but are not significant. These results differ to those in (Mumo, 2017) study on the Nairobi stock exchange where money supply is negatively related to stock prices and exchange rate is positively associated. There is only 0.87% in terms of long term causality and there is no short run causality on closing price derived from money supply, inflation, interest rates. In addition, bidirectional causality between closing price and exchange rate was determined through Granger causality tests. All the lagged macroeconomic variables combined granger cause closing price. The OLS results exhibit that 89.7% variation in closing price is explained by the macroeconomic variables used in the study. OLs results show that money supply is positively associated with closing prices whilst exchange rate,

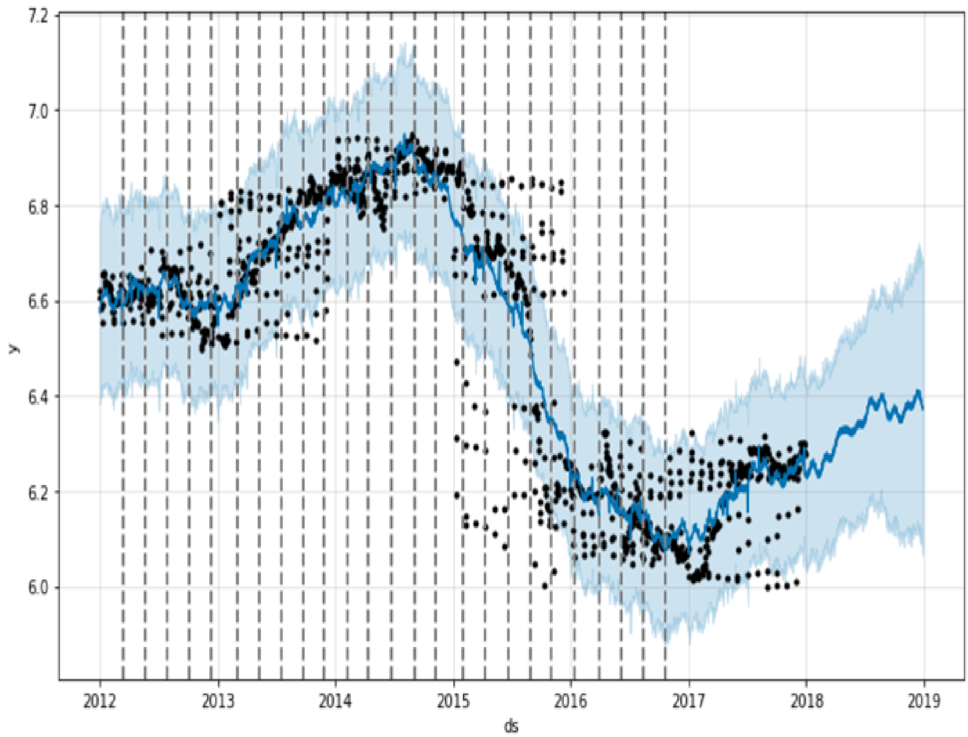

FIGURE 6.18: Graphical Representation of GAM Results for Lusaka Stock Exchange

inflation and interest rates are all negatively associated as shown in equation 30.

lnclose=-9.556+2.392lnm2-2.789lnexr-2.165lncpi-0.441lnint With regards to the Mauritian bourse, only three economic variables were considered to explain the relationship between closing price and macroeconomic variables as follows;

$$\text{lnclose}=3.287-2.241\text{lnexr}+1.707\text{lncpi}+0.217\text{lnint}$$

Vector Autoregression results show that there is a positive association between closing price, inflation and interest rates whilst a negative relationship is noticeable for exchange rate. OLS results also show an 80.6% variation of closing price as explained by the three macroeconomic variables. All the combined lagged macroeconomic variables were able to grange cause closing price. A unidirectional causality was found through closing price granger causing interest rates and exchange rate.

Different results are noticeable for Morocco which exhibits negative relations between all variables to closing price with an R^2 of 66.5% as shown below. No significant long run relationship was noticeable for Moroccan bourse and there were no significant short term causality relationships. Granger causality results show that closing price can granger cause inflation.

$$\text{lnclose}=21.75-0.268\text{lnm2}-0.337\text{lnexr}-2.228\text{lncpi}$$

In the Nigerian bourse, a long run relationship showing association between variables is identified though not significant. Hence, in the long run, macroeconomic variables cannot explain movement in closing prices. Granger causality also shows that no causality was found between closing price and the macroeconomic variables. Unlike (Okoro, 2017) study results where an R^2 of 27.8% was attained to

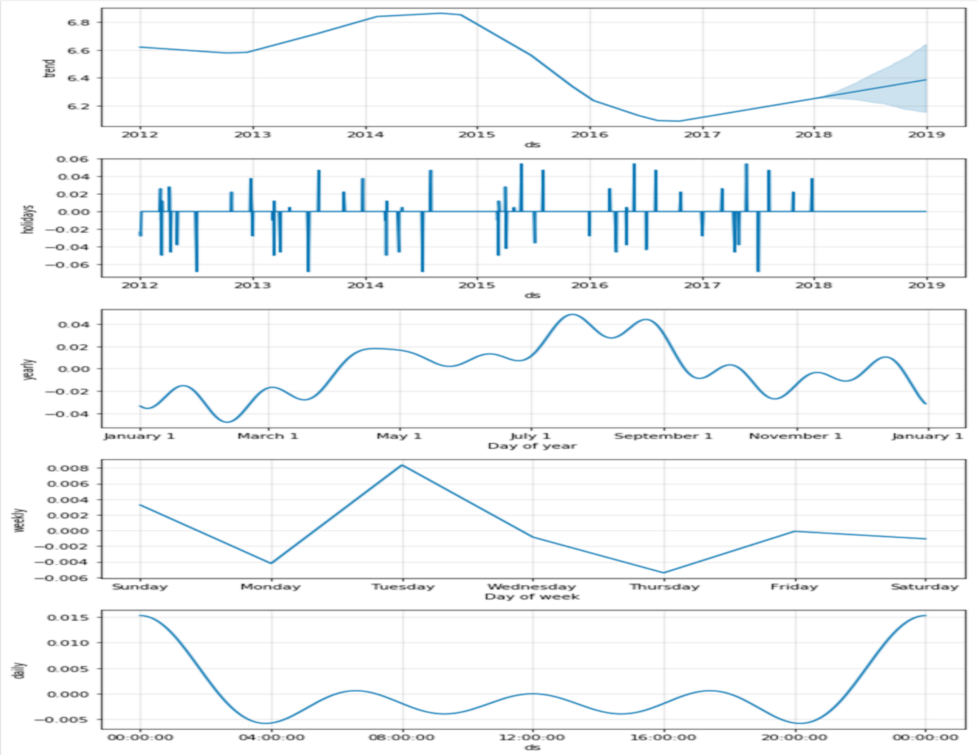

FIGURE 6.19: Seasonal Components of the Time Series for Lusaka Stock Exchange

explain effect of macroeconomic variable on stock prices, the OLS results show that money supply is positively associated to closing price whilst negatively associated to all other variables with an R^2 of 83.8

$$lnclose = -28.15 + 3.064lnm2 - 0.961lnexr - 2.551lncpi + 0.0060lnint$$

South Africa's two cointegration equations show evidence of long run association between closing price and macroeconomic variables though both are not statistically significant. Unidirectional granger causalities from money supply to closing price, closing price to inflation and from closing to interest rates was noticeable for South Africa. Bidirectional causality on closing price and exchange rate was also noticeable. The OLS results show a 94.3% variation in closing price as influenced by the macroeconomic variables. Similarly to Nigeria, Egypt and Kenya, closing price is significantly positively associated to money supply and all other variables are negatively associates.

$$lnclose = -6.098 + 1.502lnm2 - 0.604lnexr - 1.059lncpi - 0.426lnint$$

A weak relationship is noticeable for the Tunisian bourse with closing price variation to macroeconomic variables at a low R^2 of 15.2%. Granger causality results show a unidirectional causality from inflation to closing price. Unidirectional causalities from inflation to closing price and closing price to exchange rate were found for the Zambian bourse. However a bidirectional causality between closing price and inflation was noted for the Zimbabwean bourse. Similarly, the Zimbabwe's bourse is significantly influenced by inflation though the R^2 is low at 18.2%. For the Zambian bourse, money supply and interest rates positively influences stock price movements whilst exchange rate and inflation negatively influence closing price. An R^2

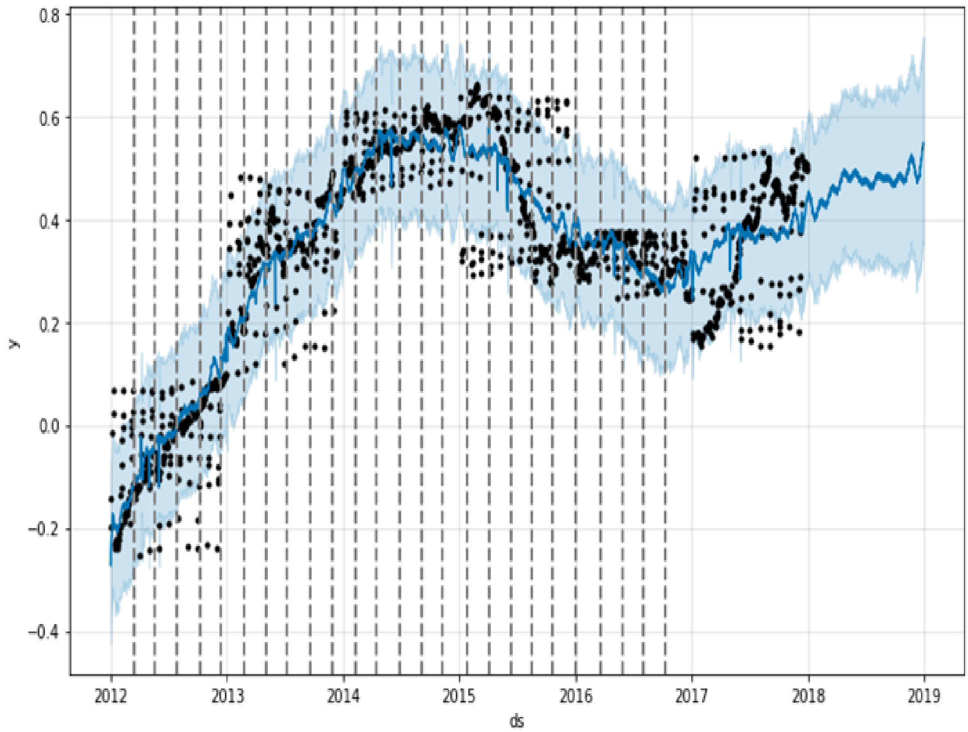

FIGURE 6.20: Graphical Representation of GAM Results for Nairobi Stock Exchange

of 88.1% is reported for the Zambian bourse. OLS equations for Tunisia, Zambia and Zimbabwe are as follows;

$$lnclose = 1.040 + -1.100lnexr + 1.574lncpi$$
$$lnclose = -3.680 + 2.123lnm2 - 1.539lnexr - 1.918lncpi + 0.265lnint$$
$$lnclose = -7.141 + 2.607lncpi$$

With reference to table 6.10, money supply is positively associated with closing prices as found in other studies (Barakat et al., 2016; Eita, 2012; Chia and Lim, 2015) . The positive money supply –stock return relationship found in this study implies that increases in money supply lead to increased cash flows whereby investors can buy more stocks, resulting in share price and stock return increases. In other words, the increases in share prices is influenced by economic stimulus provided by money growth. This is in support with the portfolio theory which suggest that increases in money supply cause a portfolio shift from non-interest bearing money to financial assets including shares. Such expansionary monetary policy has an effect on share price increase, hence stock market returns. Expansionary monetary policy aimed at stimulating economies, posits that an increase in money supply causes an unexpected boost in the public's cash balances resulting in a wealth effect. Such an effect tends to stimulate consumption and increase investment.

The positive link between monetary supply and stock returns corroborates with the Lucas theory of economic growth. This research findings in this study are in agreement with findings for the Kenyan stock market (Mumo, 2017) and for the Turkish stock market (Rjoub et al., 2017) , Taiwan stock exchange (Chen et al., 2005) ,BSE-India (Kotha and Sahu, 2016) , Malaysia (Chia and Lim, 2015) , US and Canada -(Bhuiyan and Chowdhury, 2019) . Evidence from this study contrasts findings by

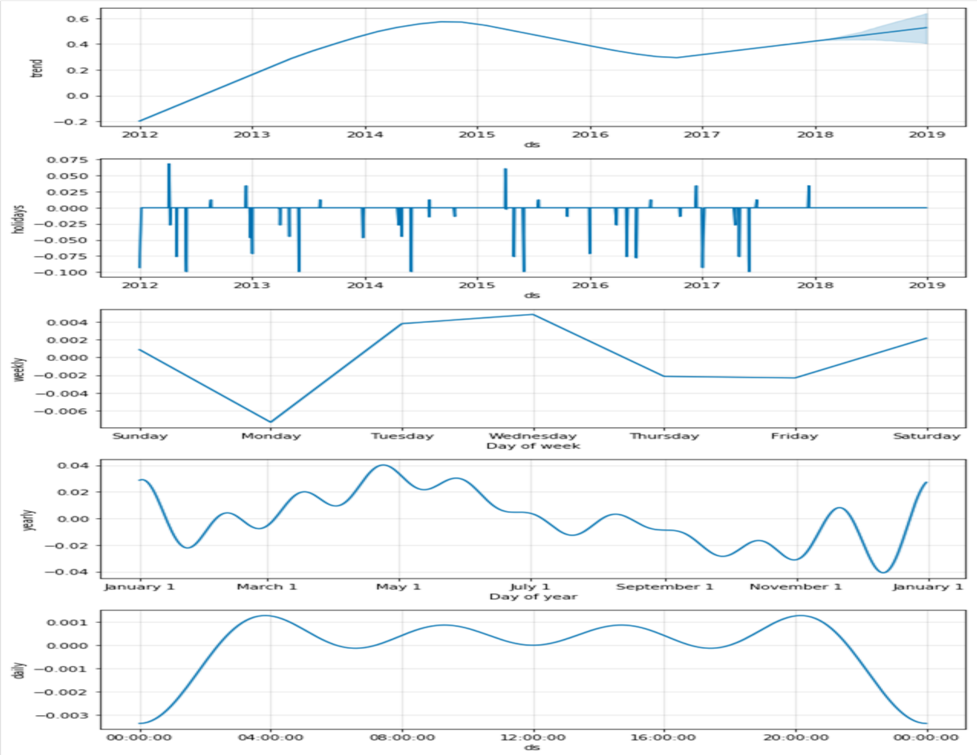

FIGURE 6.21: Seasonal Components of the Time Series for Nairobi Stock Exchange

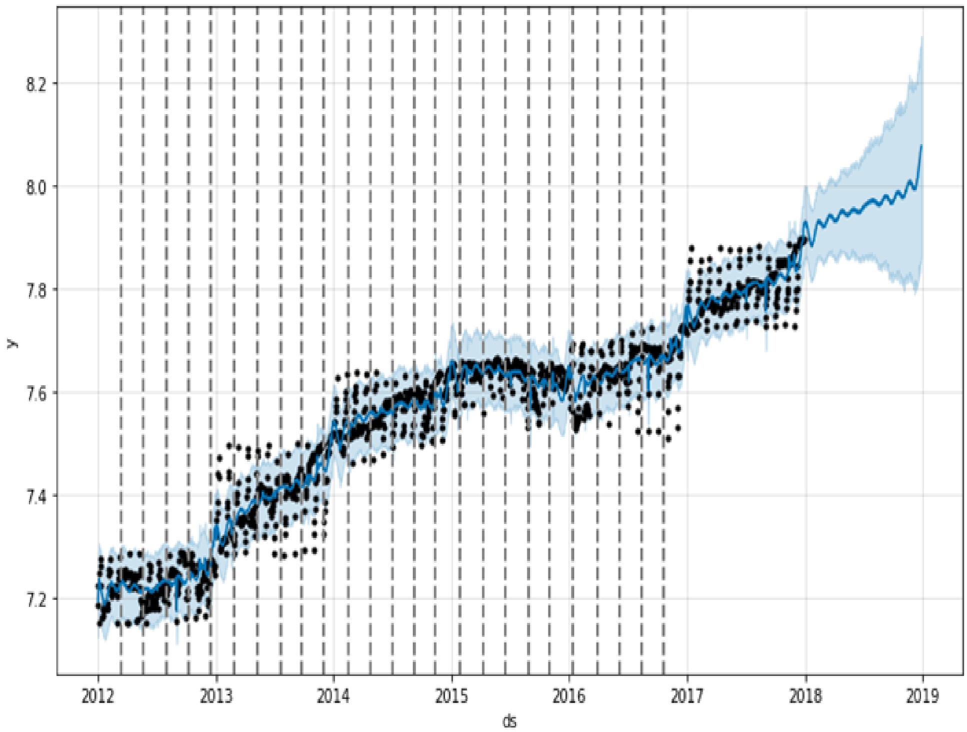

FIGURE 6.22: Graphical Representation of GAM Results for S&P 500

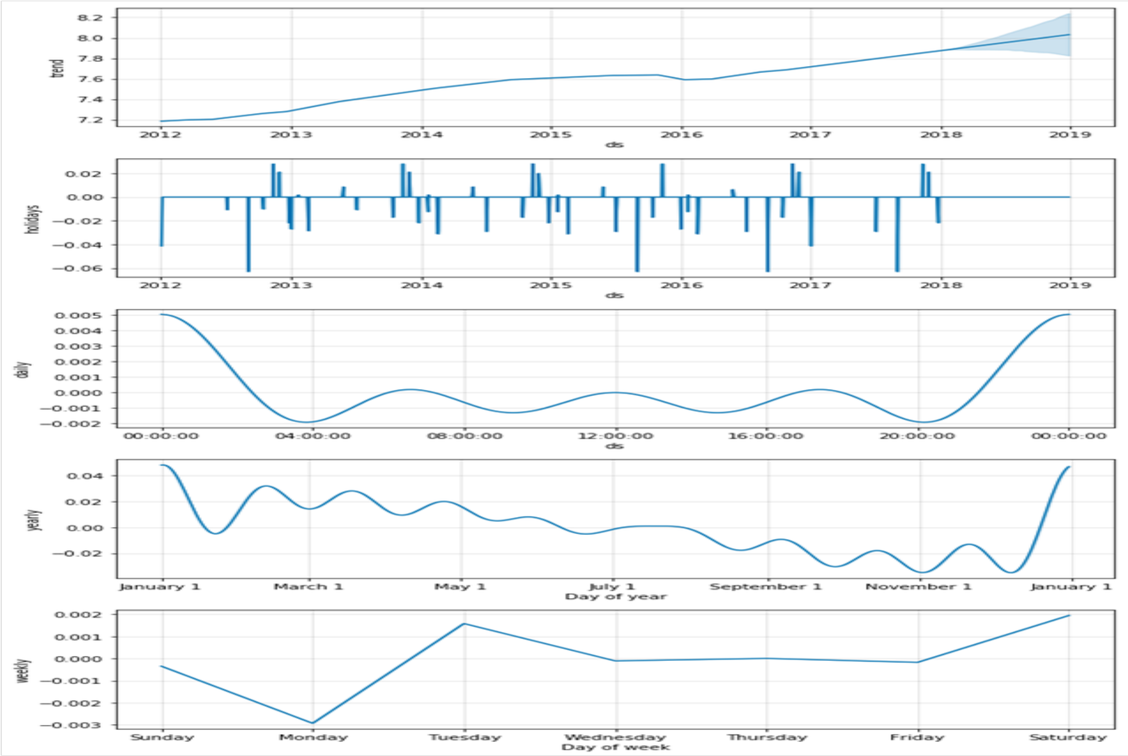

FIGURE 6.23: Seasonal Components of the Time Series for S&P 500

(Okoro, 2017) on the Nigerian stock market were money supply was negatively related to stock market performance.

Overally, a negative relationship between stock prices and inflation was noted for all countries in this study except for Mauritius, Tunisia and Zimbabwe. An increase in inflation causes a reduction in closing prices and returns. Thus equities cannot be used as a hedge against inflation. The negative relationship is in line to Eita's findings on the Namibian bourse. Similar results for the Mauritian and Tunisian bourse were found out for the BSE Sensex, India (Kotha and Sahu, 2016) , US markets (Jareno and Negrut, 2016) , Nigerian stock market (Okoro, 2017) where inflation was positively linked to stock prices.

Evidence from this research is in line with the Fama's proxy effect hypothesis which states that the negative relationship between inflation and real activity induces the spurious negative correlation between equity returns and inflation for the African stock markets under consideration. In addition, this research evidence of a positive relationship between inflation and stock prices for Tunisia is in contrast to (Barakat et al., 2016) findings that found a negative relationship for the same stock market.

All the countries under study report a negative relationship between closing prices and exchange rate. The negative relationship between stock returns and exchange rate affects the level of international investment. As exchange rate increases, stock prices reduce according to the study results. Large shocks in the exchange rate will adversely affect stock returns. Hence, a need for policy makers to pursue policy aimed at stabilising the exchange rate is a must. For the investors and market practitioners, this study points to the fact that exchange rate is an unavoidable risk which should be considered when formulating hedging and portfolio selection strategies.

The results in agreement with (Lawal et al., 2016) findings on the Nigerian stock

TABLE 6.27: Augmented Dickey Fuller Unit root tests results

Index	Variable		Level	First Difference	Index	Variable		Level	First Difference
Botswana	lnClose	t-statistic	-1.476	-7.516	Nigeria	lnClose	t-statistic	0.026	-7.212
		prob	0.5451	0.0000			prob	0.9606	0.0000
	lnCPI	t-statistic	-3.642	-8.477		lnCPI	t-statistic	1.339	-5.051
		prob	0.0050	0.0000			prob	0.9968	0.0000
	lnExr	t-statistic	-0.4087	-10.281		lnExr	t-statistic	0.813	-6.630
		prob	0.9088	0.0000			prob	0.9918	0.0000
	lnInt	t-statistic	-0.223	-7.579		lnInt	t-statistic	-2.499	-6.982
		prob	0.9357	0.0000			prob	0.1158	0.0000
	lnM2	t-statistic	-1.8987	-10.001		lnM2	t-statistic	-1.770	-9.209
		prob	0.3331	0.0000			prob	0.3953	0.0000
Egypt	lnClose	t-statistic	-0.575	-10.792	South Africa	lnClose	t-statistic	-0.934	-12.378
		prob	0.8765	0.0000			prob	0.7767	0.0000
	lnCPI	t-statistic	4.464	-6.650		lnCPI	t-statistic	0.525	-9.320
		prob	1.0000	0.0000			prob	0.9856	0.0000
	lnExr	t-statistic	0.990	-13.987		lnExr	t-statistic	-0.783	-11.118
		prob	0.9942	0.0000			prob	0.8242	0.0000
	lnInt	t-statistic	-0.158	-12.729		lnInt	t-statistic	-1.103	-10.885
		prob	0.9433	0.0000			prob	0.7139	0.0000
	lnM2	t-statistic	2.219	-11.394		lnM2	t-statistic	-2.001	-14.944
		prob	0.9989	0.0000			prob	0.2862	0.0000
Kenya	lnClose	t-statistic	-1.202	-8.398	Tunisia	lnClose	t-statistic	-2.278	-10.353
		prob	0.6726	0.0000			prob	0.1791	0.0000
	lnCPI	t-statistic	-0.164	-5.094		lnCPI	t-statistic	-0.341	-10.044
		prob	0.9427	0.0000			prob	0.9195	0.0000
	lnExr	t-statistic	-0.712	-6.304		lnExr	t-statistic	0.953	-8.759
		prob	0.8436	0.0000			prob	0.9937	0.0000
	lnInt	t-statistic	-1.060	-6.084		lnInt	t-statistic	-	-
		prob	0.7306	0.0000			prob	-	-
	lnM2	t-statistic	-2.603	-10.930		lnM2	t-statistic	-	-
		prob	0.0924	0.0000			prob	-	-
Mauritius	lnClose	t-statistic	-2.949	-7.903	Zambia	lnClose	t-statistic	-0.491	-5.558
		prob	0.0399	0.0000			prob	0.893	0.0000
	lnCPI	t-statistic	-3.387	-9.419		lnCPI	t-statistic	1.278	-3.606
		prob	0.0114	0.0000			prob	0.9965	0.0056
	lnExr	t-statistic	-1.639	-11.753		lnExr	t-statistic	-0.826	-6.969
		prob	0.4625	0.0000			prob	0.8115	0.0000
	lnInt	t-statistic	0.419	-11.258		lnInt	t-statistic	-1.671	-5.189
		prob	0.9822	0.0000			prob	0.4460	0.0000
	lnM2	t-statistic	-	-		lnM2	t-statistic	-0.902	-7.289
		prob	-			prob	0.7872	0.0000	
Morocco	lnClose	t-statistic	-1.427	-9.152	Zimbabwe	lnClose	t-statistic	-3.464	-8.596
		prob	0.5692	0.0000			prob	0.0090	0.0000
	lnCPI	t-statistic	-0.807	-7.010		lnCPI	t-statistic	-0.467	-6.523
		prob	0.8172	0.0000			prob	0.8983	0.0000
	lnExr	t-statistic	-0.792	-10.450		lnExr	t-statistic	-	-
		prob	0.8216	0.0000			prob	-	-
	lnInt	t-statistic	-	-		lnInt	t-statistic	-	-
		prob	-	-			prob	-	-
	lnM2	t-statistic	-0.455	-7.562		lnM2	t-statistic	-	-
		prob	0.9005	0.0000			prob	-	-

market and contradict findings by (Gay, 2016) for Brazil, Russia and China,(Mumo, 2017) for Nairobi, (Kotha and Sahu, 2016) for BSE Sensex Karachi-Pakistan and (Okoro, 2017) for Nigeria where a positive relationship was found. The governments of the countries under consideration can formulate policy that can induce more investments in the equity markets and make them a vital resource mobilisation channel for economic growth.

Interest rate increases result in a reduction of share prices and otherwise. The higher the interest rate, the less valuable is the cash flow after discounting, hence may result in reduced investment and reduced stock market returns. When interest rates increase, there is a shift investment from stocks to the bank which leads to stock price reduction. In other words, contractionary monetary policy through increased

TABLE 6.28: Multivariate Regression results

Variables	Egypt	Kenya	Mauritius	Morocco	Nigeria	South Africa	Tunisia	Zambia	Zimbabwe	Botswana
lnm2	5.592***	2.392***	-	-0.268	3.064***	1.502***	-	2.123***	-	0.676***
	(0.466)	(0.158)	-	(0.283)	(0.412)	(0.106)	-	(0.193)	-	(0.203)
lnexr	-2.210****	-2.789****	-2.241***	-0.337*	-0.961***	-0.604***	-1.100***	-1.539***	-	-0.515***
	(0.359)	(0.209)	(0.111)	(0.190)	(0.172)	(0.0726)	(0.244)	(0.156)	-	(0.136)
lncpi	-5.473***	-2.165***	1.707***	-2.228*	-2.551***	-1.059***	1.574***	-1.918***	2.607***	-1.257***
	(0.517)	(0.329)	(0.132)	(1.202)	(0.510)	(0.248)	(0.359)	(0.276)	(0.561)	(0.219)
lnint	-1.056	-0.441***	0.217***	-	0.00620	-0.426***	-	0.265***	-	-0.286***
	(0.649)	(0.0895)	(0.0479)	-	(0.325)	(0.0804)	-	(0.0805)	(0.107)	
Constant	-39.94***	-9.556***	3.287***	21.75***	-28.15***	-6.098***	1.040 -3.680**	-7.141***	7.327***	
	(4.818)	(1.026)	(0.637)	(2.469)	(4.994)	(0.595)	(1.580)	(1.484)	(2.608)	(1.604)
R-squared	0.752	0.897	0.806	0.665	0.838	0.943	0.152	0.881	0.182	0.488

TABLE 6.29: Summary of Closing price to macroeconomic variables relationships

	Money Supply	Exchange rate	Inflation	Interest rate	Index
Closing Price	positive	negative	negative	negative	Botswana
Closing Price	positive	negative	negative	negative	Egypt
Closing Price	positive	negative	negative	negative	Kenya
Closing Price	-	negative	positive	positive	Mauritius
Closing Price	negative	negative	negative	-	Morocco
Closing Price	positive	negative	negative	positive	Nigeria
Closing Price	positive	negative	negative	negative	South Africa
Closing Price	-	negative	positive	-	Tunisia
Closing Price	positive	negative	negative	positive	Zambia
Closing Price	-	-	positive	-	Zimbabwe

TABLE 6.30: Previous Studies on Closing Price and Macroeconomic Relationships

Author	Money Supply	Exchange rate	Inflation	Interest rate	Index
Barakat et al (2016)	positive	positive	positive	negative	Egypt
	positive	positive	negative	positive	Tunisia
Eita (2012)	positive	-	negative	negative	Namibia
Chia and Lim (2015)	positive	-	negative	positive	Malaysia
Mumo (2017)	positive	positive	-	positive	Kenya
Kotha and Sahu (2016)	positive	positive	positive	negative	Pakistan
Rjoub et al (2017)	positive	negative	positive	negative	Turkey
Paul and Malik (2003)	-	-	-	negative	Australia
Gay (2016)	-	positive	-	-	Brazil, Russia and China
Jareno and Negrut (2016)	-	-	positive	negative	USA

interest rates lowers level of investment and results in lower stock returns. Governments can also implement an expansionary monetary policy by reducing interest rates. This reduces cost of borrowing, hence serving as an incentive for firms who in turn respond by increasing their stock investments. The evidence found in this study is in agreement with research evidence found in Egypt (Barakat et al., 2016),Turkish stock markets (Rjoub et al., 2017), Colombo stock exchange (Amarasinghe, 2015), BSE-India (Kotha and Sahu, 2016), the Australian market (Paul and Malik, 2003), European economies (France, Germany, UK) – (Peiro, 2016), US markets (Jareno and Negrut, 2016), US and Canada (Bhuiyan and Chowdhury, 2019) implying that frontier, emerging and developed nations all experience a negative relationship between interest rates and stock returns. Unlike results for Nigeria (Okoro, 2017) in which exchange rate is negatively associated with closing price, this current study found a positive relationship.

A key conclusion is that the macroeconomic variables considered for this research affect each stock market differently. However, all markets closing prices are negatively influenced by exchange rate. The other countries closing prices are negatively influenced by inflation except for Mauritius, Tunisia and Zimbabwe. Similarly, all other countries closing price indices are positively influenced by money supply except for Morocco. Such variability in reaction to macroeconomic variables also explains why the different algorithms used for prediction across these countries produced different results. In addition, the association between closing price and exchange rate for African stock markets is different as compared to developed and developing nations such as the USA, Brazil, China and Russia where a positive relationship is found. Inflation for the Dow Jones in the USA was found to be positively associated with closing price which is different for most African countries with a negative relationship.

6.16 Chapter Summary

This chapter discussed prediction results for the various countries. The findings differ from country to country proving that markets are disparate. Empirical results based on GAM, DNNs and multifactor macroeconomic models were discussed in relation to past studies. New insights are drawn from the results which can be useful to aid financial decision making and policy making by investors and government respectively.

Increased prediction accuracies were achieved in all markets under consideration through use of the newly developed financial prediction models in this research when compared to other previous studies. The models were able to predict the next day's closing price, the next day's higher and lower prices as well as market direction. Different results for GAM and DNNs in the selected stock markets though using the same financial prediction models attest to the fact that stock markets are different and influenced by varying factors inherent in the stock market's data.

Also discussed are the relationships between macroeconomic variables to stock markets which also reveal that stock markets react differently to macroeconomic variable factors. African stock markets react differently to macroeconomic factors when compared to developed nations. Exchange rate and inflation are the most significant factors that negatively drive African stock markets under consideration in this research. In addition to this, notable evidence of return predictability characteristics in the selected African stock markets was noted. The presence of calendar anomalies in these markets indicates inefficiency of these markets. The next chapter concludes this research study.

Chapter 7

Summary and Conclusions

7.1 Introduction

This final chapter discusses the findings and conclude the thesis. The chapter is structured as follows; Section 7.1 introduces the chapter and section 7.2 summarizes the research findings, contributions of the study and conclusion of the research whilst section 7.3 covers potential future research.

7.2 Summary and Conclussion

This study was mainly concerned with the development of prediction models to forecast African stock market movements, determine the variables that are largely responsible for stock market movements in Africa, determine if these factors influence African Stock Market share prices differently and determine if African markets are inefficient through calendar anomalies. The focus of this research was on 10 African stock markets namely; Botswana Stock Exchange (Botswana), Egypt Stock Exchange (Egypt), Nairobi Stock Exchange (Kenya), Stock Exchange of Mauritius (Mauritius), Moroccan Stock Exchange (Morocco), Nigerian Stock Exchange (Nigeria), Johannesburg Stock Exchange (South Africa), Tunisia Stock Exchange (Tunisia), Lusaka Stock Exchange (Zambia) and Zimbabwe Stock Exchange (Zimbabwe). These markets were compared to the SP500 for prediction capabilities. The comprehensive and comparative approach of this study between unidirectional, bidirectional and statistical algorithms in stock market prediction contributed immensely to literature on stock market prediction and yielded evidence based investment and trading decision making capabilities.

Special consideration was given to various prediction modelling techniques that would improve on prediction accuracy for the African stock markets. To this end, the study implemented the following prediction techniques; the Generalized Additive Model (GAM) and six deep neural networks namely Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), Gated Recurrent Neural Network (GRU), Bidirectional Recurrent Neural Network (BRNN), Bidirectional Long Short Term Memory (BLSTM), Bidirectional Gated Recurrent Neural Network (BGRU). The work done in this study can be divided into two empirical thematic areas. To start with, a pursuit to verify the predictability of African stock markets was considered important. Second, the study sought to determine which macroeconomic variables influence the movement of African stock markets.

The key conclusion of this thesis is that African stock markets are predictable with a degree of high certainty even though they are believed to be inefficient, volatile, illiquid and chaotic. Using deep neural network (DNN) algorithms namely RNN, LSTM, GRU, BRNN, BLSTM and BGRU and a statistical GAM algorithm, which are explicitly explained in chapter 4, the analysis results in chapter 6 revealed most prediction accuracies are in the +90% range with only a few exceptions in the 60-80% range. It can be concluded that amongst the key contributions of this research, deep neural networks can be used for financial time series prediction. DNN algorithms are suitable for financial forecasting other than being used for speech-to-gesture generation, learning fashion compatibility, video description, image captioning, handwriting recognition, sequence-based problems and automatic speech recognition acoustic models. A resounding success of the DNN prediction accuracies provides new trading and investment insights to the African stock market arena.

In addition, GAM algorithms predicted African stock markets better than the Deep Neural Networks. It can be concluded that GAM models are better predictors than deep neural networks for African Stock Market and US stock market predictions. Not only do they predict future prices with high accuracy but they are also able to forecast the direction of the stock market.

In consideration of deep neural networks only, the best performing algorithm is the LSTM as evidenced by the high prediction accuracies as detailed in chapter 6.The 3 gate system of LSTMs comprising of input gate, forget gate and output gate yields better prediction results than the 2 gate system of GRUs and no gate system for RNNs. Also in addition, depending on the stock market, simple deep neural networks such as RNN, LSTM and GRU at times outperformed the bidirectional deep architectures. Therefore, it is not straight forward that bidirectional deep networks are always better than unidirectional architectures. The deployment of deep neural networks to stock market forecasting in African markets according to this research findings prove that there is no major supremacy in the use of bidirectional deep neural networks in stock market prediction when compared to unidirectional deep neural networks.

The deployment of deep neural networks and GAM to African stock market prediction provides new insights to stock market direction movements which are beneficial to traders and investors. Another key contribution of this study is the use of GAM for calendar anomaly detection. This is the first study to ascertain calendar anomaly detection with remarkable success as evidenced by the high prediction accuracy attained. Academia and Industry can make use of market direction guidelines from the prediction models to take trading positions, stock price resistance and support levels. GAM results also reveal the highest and lowest return possibilities for each country. Hence, trading rules and recommendations can thus be effected for the various markets to either go long when the market is at its lowest and go short when it is at its highest. Similar trends can also be noted in certain countries; hence investors can use the same trading policy in such markets.

Stock markets are disparate as evidenced by different trends and seasonality's exhibited in the results and finding section in chapter 6. Except for South Africa, Mauritius and Morocco, all the other countries exhibit different weekly trends. As for year trends, all countries displayed different trends and seasonality's. The GAM results from this study can contribute immensely to the theory of the day of the week effect and month on month effects knowledge on stock market asset returns. Given the varying week and monthly effects for each country, regulatory agencies can formulate policies to control markets to avoid either excessive buying or selling as traders and investors make use of the calendar anomaly results for arbitraging purposes.

Findings in this research rejects the Efficient Markets Hypothesis as stock markets are predictable and with high accuracy. Arbitraging opportunities are existent in African stock markets. Such high prediction accuracies can be capitalized on by investment professionals as they can use the prediction models to arbitrage in the stock markets. Hence, this cements on the key concept of Adaptive Markets Hypothesis and enhance the chances to attain great financial gain for investors and traders. In addition, the prediction models used in this research were able to predict African stock markets, which are well known for their complexity owing to varying trading, economic and political environments which affect the stock market. Hence, the prediction models are giving more evidence that complex environments such as stock markets are indeed predictable according to the Complex Adaptive Systems Theory. The existence of arbitraging opportunities can be an attractive force for both domestic and international investors and in turn lead to economic growth for the selected African countries in this study.

Macroeconomic variables (money supply, inflation, interest rates and exchange rates) used in this study gave varying results for each country. A negative relationship between exchange rates with stock returns in the ten countries considered for this research is determined. This advances the Arbitrage Pricing Theory by showing the various effects; macroeconomic variables (k-factors) have on closing stock price. It is therefore paramount to conclude that with regards to macro-economic impact on stock prices, African markets are influenced differently when compared to other emerging markets and developed markets for all macroeconomic variables. Mixed results were noted for inflation and interest rates for the African countries in comparison to other stock markets globally.

Such results at country level can be useful for policy making. In order to take on either an expansionary or contracting monetary policy positions, governments in the respective countries can either increase money supply or interest rates respectively. Policy makers should maintain an appropriate rate of interest in each country that helps and motivates investors. Stock prices can also be used as leading indicators for macroeconomic variables in each respective country except for Botswana, Tunisia and Zimbabwe.

It thus imperative that governments and stock market regulators consider the association between the stock market and macroeconomic variables as this leads to a more stable market. For example, government should monitor and control inflation as it has negative effects on closing share prices. In addition, government policy on exchange rate control is also important as this greatly affects level of foreign investment. For traders and investors, this study recommends that exchange rate should be considered as a vital source of unavoidable risk when formulating hedging and portfolio selection strategies. International investors can also hedge against foreign currency exposure and loss of returns by monitoring the exchange rate. In a nutshell, experimental evidence in this study points to the fact that an improvement in the domestic macroeconomic climate is important in explaining stock price movement, and in turn, stock returns.

In a nutshell, this study concludes that stock markets inclusive of African stock markets are predictable. Second, each stock market is affected differently by varying macroeconomic factors with exchange rate negatively influencing the majority of all stock market indices closing prices considered in this research. A disparity was also noted in that the selected macroeconomic variables used for this research affected African stock markets differently as compared to the effect on the S P500. Finally, it can be concluded that African stock markets are inefficient owing to return prediction capabilities found in the stock markets through use of GAM, RNN,GRU, LSTM, BRNN, BGRU and BLSTM prediction models.

7.3 Future Research

While there is increasingly vast research in developed and other developing countries, little evidence on stock market predictions exists for Africa. This study made use of deep neural networks using absolute prices only. However, future studies can also include other factors such as news information, and micro economic factors in model development. In addition to the five macroeconomic factors used in addressing the second part of this research, more macroeconomic variables such as industrial production can also be constituted. Lastly, similar week effects for South Africa, Mauritius and Morocco were noticeable with lowest and highest returns on Wednesday and Tuesday. Further research to ascertain if there is co-movement between these markets can be done. An extension of this work in developed stock markets can also add on to the existing knowledge of stock market predictions whilst comparing the output to emerging and frontier stock markets covered in this study.

Appendix A

PUBLICATIONS 1

Predicting Emerging and Frontier Stock
Markets Using Deep Neural Networks

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Abstract. Investors, researchers and finance practitioners are continu- ously looking for the best technique that can assist them in accurately predicting the stock markets. The ability to predict stock prices con- tradicts the efficient market hypothesis (EMH) and can yield substantial monetary rewards for investors. Various stock price prediction techniques are used to predict the stock market and they range from statistical to machine learning methods. Statistical models fall short in handling non- linear data which characterizes most stock markets. Artificial Neural Networks (ANNs), one of the widely used techniques are able to handle nonlinear data but have low prediction accuracy due to their inability to handle long term dependencies and memory capacity handling. Predic- tion models that have an ability to learn long-term dependency informa- tion are ideal for stock market prediction. The current study uses deep learning techniques, namely, Long Short Term Memory (LSTM), Recur- rent Neural Networks (RNNs), Gated Recurrent Units (GRUs), Bidirec- tional LSTM (BLSTM), Bidirectional RNN (BRNN), Bidirectional GRU (BGRU) to predict stock markets in ten sub-Saharan African countries. The prediction techniques were run on a python 3.5 environment using Theano and Keras libraries. Limited computing capacity was of great concern. However, for the purpose of this study, access to high perfor- mance computing facilities was granted in order to run the experiments. Experimental results show that both unidirectional and bidirectional architectures greatly improved prediction accuracy in this research. How- ever, both architectures were found not to be significantly different in predicting the stock markets of the ten African countries. In general, LSTMs followed by BGRUs proved to be the best models in predicting the African stock markets.

Keywords: Stock prices · Prediction · Deep learning · African markets

Y. Bi et al. (Eds.): IntelliSys 2019, AISC 1037, pp. 899–918,2020. https://doi.org/10.1007/978-3-030-29516-5_68

FIGURE A.1: Publication 1

Appendix B

PUBLICATIONS 2

Stock Market Trend Prediction
in Sub-Saharan Africa Using Generalized
Additive Models (GAMs)

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Abstract. Pattern discovery emerges as a significant factor to identify the direction of the market. This study sought to test the usefulness of GAMs in predicting the frontier and emerging stock markets in Africa for pattern dis- covery by comparing its prediction capability to deep neural models namely Long Short Term Memory (LSTM), Recurrent Neural Networks (RNNs), Gated Recurrent Units (GRUs), Bidirectional LSTM, Bidirectional RNN and Bidi- rectional GRU. Using daily stock market index, the data from Bloomberg database for the period 2012 to 2018, and this study aims to predict daily closing prices for the next 365 days as well as determining the direction of the stock markets. Prediction accuracies were 99.76%, 97.55%, 100%, 99.21%, 99.50%, 99.32%, 99.58%, 99.88%, 99.59% and 99.52% for Botswana, Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tunisia, Zambia and Zimbabwe stock markets respectively. The GAM model outperformed the deep neural models and it can be used for enhancing investment decision making in Africa.

1 Introduction

The field of stock market forecasting has and is still receiving substantial notice from both practitioners as well as researchers as it is an essential matter for stock fund managers, individual investors and financial analysts amongst other players in the stock markets [1]. The ability to correctly predict future market trends according to [2] is a prerequisite for successful financial market trading. In [3], the authors believe that the success of market trading strategies depends upon the accurate predictions of Stock price movements. Those who will win in today's business world are those with the ability to predict the future, or at least having some future information upon which they can support their decisions [4]. Generally, Stock markets are described in [5] as complex, evolutionary and nonlinear dynamic systems whose prediction is considereda challenging task.

A. P. Pandian et al. (Eds.): ICICCS 2019, AISC 1039, pp. 9–19, 2020. https://doi.org/10.1007/978-3-030-30465-2_2

FIGURE B.1: Publication 2

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