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Revolutionising Electricity Theft Detection in Smart Grids: An Edge-Centric Hybrid Machine Learning Framework with IoT Integration

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Revolutionising Electricity Theft Detection in Smart Grids: An Edge-Centric Hybrid Machine Learning Framework with IoT Integration

A Dissertation submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in fulfillment of the requirements for the degree of Master of Science in Engineering.

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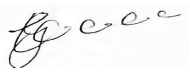
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Declaration

I, Malebo Legologela Gift Maboko, hereby declare that the Dissertation titled "Revolutionising Electricity Theft Detection in Smart Grids: An Edge-Centric Hybrid Machine Learning Framework with IoT Integration" submitted for Master of Science in Engineering at the University of the Witwatersrand is my original work, except where otherwise acknowledged.

Signature: 

Date: 10/07/2025

Abstract

Non-Technical Losses (NTLs), including electricity theft, meter tampering, and incorrect readings, significantly contributed to distributed electricity losses, accounting for nearly half of global losses resulting in substantial financial impacts annually. To address this issue, the study proposed a robust anomaly detection framework that integrated smart meters and Advanced Power Metering Infrastructure (APMI) with machine learning models to identify fraudulent energy consumption. Preprocessing techniques, such as data interpolation, Z-score Analysis, data normalisation, and Principal Component Analysis (PCA), were employed to handle inconsistencies, missing values, and outliers, ensuring accurate feature extraction and classification. A supervised learning approach was implemented, utilising Deep Neural Networks (DNN), Random Forest (RF), Logistic Regression, and a custom Hybrid Random Forest-DNN model. The models were trained and evaluated on publicly available smart meter data, augmented with synthetic anomalies at 25%, 50%, and 75% levels to assess robustness. The Hybrid RF-DNN model outperformed others, achieving an average F1-score of 96%, a test accuracy of 96.6%, and a low root mean squared error (RMSE) of 0.2065. It also reduced execution time by 14.3% compared to the standard Random Forest model. The Random Forest model followed closely, with an F1-score of 95.0% and test accuracy of 95.1%. Independent DNN models achieved an average F1-score and test accuracy of 92.6%, while Logistic Regression performed the weakest, with an F1-score of 65% and accuracy of 64.2%. A Flask-based web application was developed for real-time anomaly detection, integrating automated data preprocessing, model deployment, and interactive visualisation. Additionally, a microcontroller-based transducer system was designed in an attempt to mitigate physical theft. The system, featuring an ESP32 microcontroller, Global System for Mobile Communications (GSM) module, sound sensor, and ultrasonic sensor, was optimised for Zone 2 environments and generated Short Message Service (SMS) alerts with a response time of 3.9 seconds. Future work aimed to explore explainable Artificial Intelligence (AI) methods, such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), alongside unsupervised learning techniques like k-means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN), to enhance anomaly detection and model interpretability.

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List of Publications

The second research paper received the first-place award in the Artificial Intelligence-Machine Learning category at the conference.

1. Maboko M, Dewa M, Design and Implementation of a Smart Transducer System Prototyping of a Micro-controller Based Intelligent Electrical Equipment Theft Detection Methodology. Proceedings of the 1st Australian International Conference on Industrial Engineering and Operations Management 2022 Dec 21, https://doi.org/10.46254/AU01.20220553.
2. Maboko M, Dewa M, Securing Mobile Connectivity: A Data-Driven Approach for Detecting Electricity Theft and Anomalies in 4G and 5G Telecommunications Base Stations. Proceedings of the 15th International Conference on Industrial Engineering and Operations Management Singapore, February 18-20, 2025, In press.

This dissertation expands upon the foundational research presented in these two conference papers, advancing the work by enhancing its practical applicability and robustness.

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List of Abbreviations

AI Artificial Intelligence
ANN Artificial Neural Network
APMI Advanced Power Metering Infrastructure
AUC Area Under the Curve
AUC-ROC Area Under the Receiver Operating Characteristic Curve
CNN Convolutional Neural Network
dBA Decibels Adjusted (sound intensity unit)
DBSCAN Density-Based Spatial Clustering of Applications with Noise
DNN Deep Neural Network
EDA Exploratory Data Analysis
GPRS General Packet Radio Service
GSM Global System for Mobile Communications
HTTP HyperText Transfer Protocol
IIoT Industrial Internet of Things
IoT Internet of Things
IQR Interquartile Range
kNN k-Nearest Neighbors
LIME Local Interpretable Model-agnostic Explanations
LR Logistic Regression
LSTM Long Short-Term Memory
ML Machine Learning
NAS Neural Architecture Search
NC Normally Closed (relay configuration)
NO Normally Open (relay configuration)
NTL Non-Technical Loss
PCA Principal Component Analysis
PMU Phase Metering Unit
ReLU Rectified Linear Unit
RF Random Forest
RL Reinforcement Learning
RMSE Root Mean Squared Error
ROC Receiver Operating Characteristic
RNN Recurrent Neural Network
SGD Stochastic Gradient Descent
SHAP SHapley Additive exPlanations
SMS Short Message Service
SMU System Management Unit
SVM Support Vector Machine
SVR Support Vector Regression
TL Technical Loss
TPU Tensor Processing Unit
VCC Voltage at the Common Collector (power supply pin)
GND Ground (electrical reference point)

List of Symbols

A Desired amplitude in sound signal preprocessing (Equation 4.1)
b Bias term in machine learning models (Equations 2.1, 2.5, 2.9)
c Speed of sound, 343 m/s in acoustic path modelling (Section 4.3.1)
C Regularisation parameter in Support Vector Machine (Equation 2.5)
d Number of features in k-Nearest Neighbors distance calculation (Equation 2.4)
e Base of the natural logarithm in Logistic Regression (Equation 2.2)
$f(\cdot)$ Function mapping inputs to outputs in supervised learning (Equation 2.1)
$H(s)$ Transfer function of the smart transducer system (Equations 4.5, 4.6, 4.7)
$H_{mic}(s)$ Transfer function of the microphone in smart transducer system (Equation 4.1)
$H_c(s)$ Transfer function of the control system in smart transducer system (Equation 4.2)
$H_r(s)$ Transfer function of the relay in smart transducer system (Equation 4.3)
$H_{acoustic}(s)$ Transfer function of the acoustic path in smart transducer system (Equation 4.4)
$I(\cdot)$ Indicator function in k-Nearest Neighbors classification (Equation 2.3)
K System gain in smart transducer 2nd-order approximation (Section 4.3.2)
K_{mic} Microphone gain in smart transducer system (Section 4.3.1)
K_c Control system gain in smart transducer system (Section 4.3.1)
$\mathcal{L}$ Loss function in machine learning model training (Equations 2.10, 2.15)
n Number of observations in PCA and DNN training (Equations 2.13, 2.10)
N Total number of samples in a dataset (Equation 2.1)
p User-defined parameter in Minkowski distance for k-Nearest Neighbors (Equation 2.4)
$P(Y = 1)$ Probability of an event occurring in Logistic Regression (Equation 2.2)
Q_1 First quartile in Interquartile Range method (Equation 2.12)
Q_3 Third quartile in Interquartile Range method (Equation 2.12)
s Laplace variable in transfer functions (Equations 4.1–4.7)
σ Standard deviation in Z-score method (Equation 2.11); also activation function in DNN (Equation 2.9)
Σ Covariance matrix in Principal Component Analysis (Equation 2.13)
τ_m Time constant of the microphone in smart transducer system (Equation 4.1)
T_c Time constant of the ESP32 processing in smart transducer system (Equation 4.2)
τ_r Time constant of the relay in smart transducer system (Equation 4.3)
$\mathbf{V}$ Matrix of eigenvectors in Principal Component Analysis (Equation 2.14)
$\mathbf{w}$ Weight vector in Support Vector Machine (Equation 2.5); also in DNN (Equation 2.9)
w_1 First pole in the 2nd-order smart transducer system approximation (Section 4.3.2)
w_2 Second pole in the 2nd-order smart transducer system approximation (Section 4.3.2)
X Input feature vector or dataset matrix in supervised learning (Equation 2.1)
$\mathbf{X}$ Vector of input features in Support Vector Machine (Equation 2.5); also in DNN (Equation 2.9)
$x^{(i)}$ i-th input feature vector in supervised learning (Equation 2.1)
X_i i-th input vector in Support Vector Machine (Equation 2.5); also in k-Nearest Neighbors (Equation 2.4)
$X_{i,l}$ l-th feature of the i-th input vector in k-Nearest Neighbors (Equation 2.4)
$\bar{\mathbf{X}}$ Mean vector of the dataset in Principal Component Analysis (Equation 2.13)
y Output label or target value in supervised learning (Equation 2.1)
y_i i-th output label or class in supervised learning (Equation 2.1)
$\hat{y}$ Predicted output value in k-Nearest Neighbors (Equation 2.3); also in DNN (Equation 2.9)

$\hat{y}_i$ i-th predicted output value in DNN training (Equation 2.10)
α_i Lagrange multipliers in Support Vector Machine (Equation 2.6)
β_0 Intercept coefficient in Logistic Regression (Equation 2.2)
β_i Coefficients of predictor variables in Logistic Regression (Equation 2.2)
λ_i Eigenvalue in Principal Component Analysis (Section 2.6)
μ Mean of a feature or dataset in Z-score method (Equation 2.11)
$\phi(\cdot)$ Feature mapping function in Kernel PCA (Equation 2.15)
$\rho_{X,Y}$ Pearson correlation coefficient (Equation 2.14)
θ Hyperparameters in model optimisation (Equations 2.15–2.17)
θ^* Optimal hyperparameters in Grid Search and Random Search (Equations 2.15, 2.16)
ξ Tunable parameter in Bayesian optimisation (Equation 2.17)

Chapter 1

Introduction

Electricity theft within the power distribution network mainly takes place in two ways: by bypassing the energy meter and by hooking the energy line [3]. Power grids around the globe suffer from technical and non-technical losses. Technical losses (TLs) are caused by power ohmic losses in electrical components such as transformers, generators, and transmission lines [4]. Non-technical losses (NTLs) are caused by power losses that are not part of the power distribution. They are divided into two divisions, namely illegal and legal [1]. The legal NTLs include:

- Lost receipts;
- Managerial mistakes;
- Engineering technical mistakes and
- Poor installation of equipment

Furthermore, the illegal non-technical losses (NTLs) encompass:

- Illegal electrical connections;
- Fraudulent acts and
- Billing errors and irregularities

Illegal electrical connections are part of electricity theft. The electrical energy consumed by illegal connections cannot be billed since customers are also not known to the energy distribution company. Fraudulent faults include meter box tampering, corrupt meter data readings, and smart meter communication metering. Billing errors and irregularities include improper recording of electricity consumption, metering faults, and inaccurate account data [4]. Multiple factors contribute to the prevalence of NTLs, which include poor tariff structure, syndicated activities, and poor punitive action against electricity theft by the law. NTLs lead to financial losses as well as a lack of funds for the maintenance of electrical power distribution facilities. Most of the implemented power systems are not upgraded or maintained. The diagram below shows a classification of electrical power losses [1].
In South Africa, as well as many countries around the globe, there is a challenge of Non-Technical Losses (NTLs) that takes place due to electricity theft. For example, in Southeast Asia, a total of 40% of the generated power is stolen. In South Africa, billions of Rands are lost by power distribution companies every year due to the consumed electricity that is not paid for. In 2018 and 2019, a total of R 1.7 billion was lost due to technical and non-technical losses, which is an increase of 7.7% in 2018 and 8.5% in 2019 [5] [6]. Municipalities and city metropolitans form part of the electricity distribution entities in South Africa [7]. A total of over R3 billion due to NTLs only was reported by the Metros of Ekurhuleni, Tshwane, and Johannesburg in 2018 [7].
Power grids in several countries are undergoing continuous, radical upgrades. This includes the equipment of smart meters with network communication infrastructure and sensing elements that improve control and measurement capabilities, resulting in “smart” grids. This infrastructure’s major components are phase metering units (PMUs) and advanced power metering infrastructures (APMIs)[8]. A PMU is an electronic device that measures the electrical phasor (voltage and amperage) in power grids using a common source of time synchronisation. An APMI is a modernised power metering system achieved by incorporating electronic

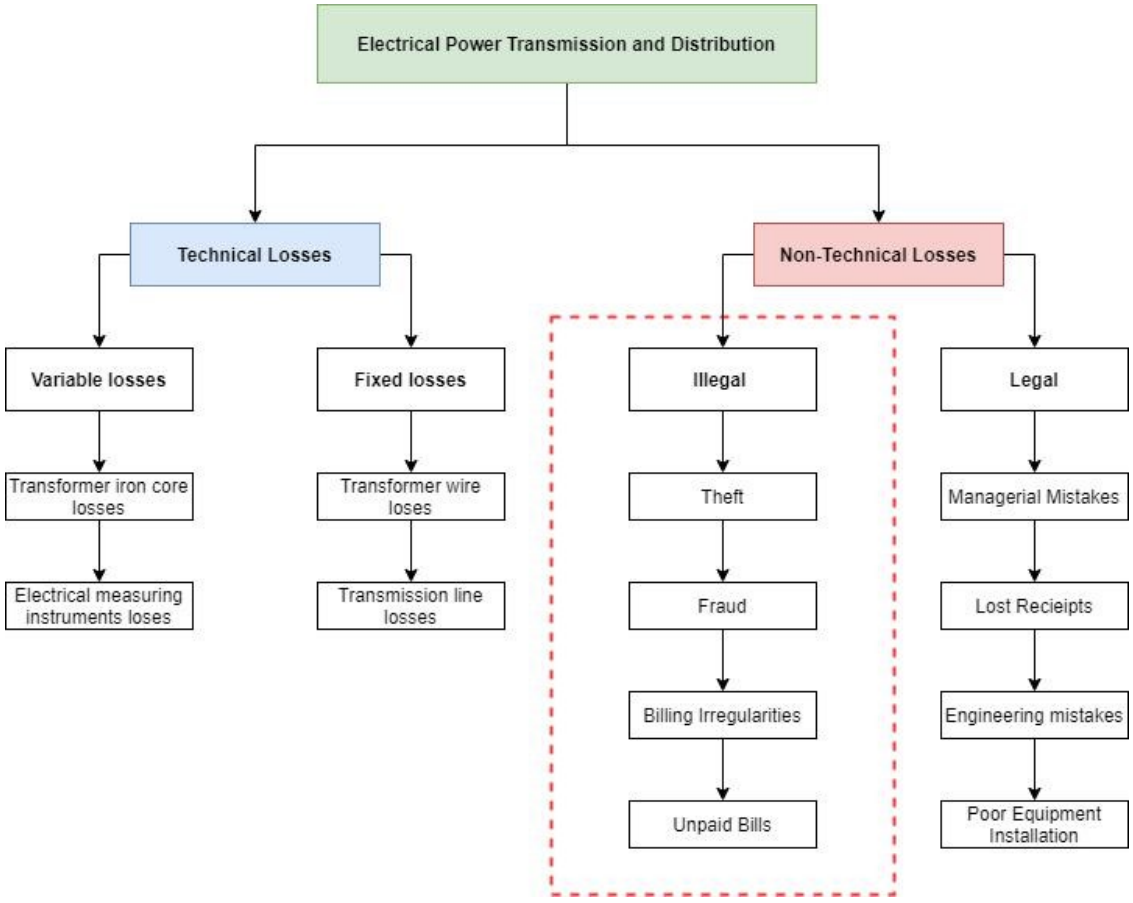


Figure 1.1: Classification of electrical power losses [1].

devices and software applications, thus replacing largely mechanical meters and leading to smart meters [8]. This research initially presents an intelligent predictive classification algorithm-based classification strategy that exploits model assessment to detect electricity theft. The results show that using model assessment techniques improves classification performance. The data used in this study was acquired from the open-source University of Massachusetts. This data consists of various electricity consumption datasets obtained from January 2016 to January 2017 [9].

This research investigates the theft of electrical equipment in enclosed spaces like networks and electrical cabinets. Equipment such as energy meters can be protected against theft and tampering.

Electricity theft within the power distribution network mainly takes place in two ways, by bypassing the energy meter and by hooking the energy line. This research focuses on electricity equipment theft in enclosed areas such as electrical and network cabinets. Enclosed electrical equipment such as battery modules and energy meters can be secured from theft and tampering.

1.1 Problem Statement

Electricity theft remains a critical challenge in power distribution networks, significantly impacting power quality, grid stability, maintenance costs, and electricity tariffs for legitimate consumers. The increasing integration of smart grids has APMI, which, while enhancing monitoring and billing efficiency, also expands the attack surface for both physical and cyber threats [10, 11].

Existing research highlights that electricity theft occurs through various means, including meter tampering, unauthorised connections to distribution feeders, and the use of electromagnetic interference to manipulate smart meter readings [10]. Furthermore, smart meters are vulnerable to cyberattacks such as wireless signal jamming, firmware manipulation, and unauthorised data access, all of which compromise the accuracy of energy consumption data [12]. Despite advancements in detection techniques, existing solutions remain inadequate, particularly in developing countries where electricity theft contributes to substantial revenue losses and economic instability.

Several scholars have proposed machine learning-based electricity theft detection systems that leverage data analytics, pattern recognition, and anomaly detection [13, 14]. However, the practical implementation of these approaches faces challenges such as high computational requirements, limited real-time processing capabilities, and susceptibility to adversarial attacks. Additionally, while some developed nations have implemented robust theft detection mechanisms, there is a lack of cost-effective and scalable solutions tailored to developing regions like Brazil and South Africa [13, 14].

1.1.1 Research Question

This study aims to address the electricity theft problem by investigating the following research question:

How best can an efficient, cost-effective, and intelligent predictive classification algorithm for detecting electricity theft while leveraging micro-controller-based techniques to enhance accuracy and real-time effectiveness be designed and implemented?

1.1.2 Key Considerations

To address this research question, the study is guided by the following considerations:

- The global rise in electricity demand has necessitated the widespread deployment of smart meters [12].
- Despite the adoption of smart grid technology, electricity theft remains a persistent issue, leading to financial losses and system inefficiencies worldwide [12].
- Existing theft detection methods are often resource-intensive, lack real-time capabilities or fail to account for the unique infrastructural challenges in developing regions [13, 14].
- There is a pressing need for a robust, dynamic, and computationally efficient detection framework that can be practically deployed in developing economies [13, 14].

1.2 Research Gap and Motivation

While prior research has explored various computational techniques for electricity theft detection such as [13, 14], few studies focus on integrating machine learning with microcontroller-based architectures to optimise performance in resource-constrained environments. This dissertation seeks to bridge this gap by developing a scalable, intelligent detection system that is both effective and feasible for real-world implementation in developing nations.

1.3 Research Objectives and Scope

The primary objective of this study is to develop a robust, cost-effective, and efficient anomaly detection framework that integrates smart meters and Advanced Power Metering Infrastructure (APMI) with machine learning models to detect electricity theft and prevent physical meter tampering. The research focuses on two key aspects: (1) intelligent predictive classification algorithms for detecting fraudulent electricity consumption and (2) a smart transducer system for mitigating physical theft of electricity equipment.

1.3.1 Objectives

The study aims to achieve the following objectives:

- Develop an effective electricity theft detection algorithm capable of reading and analysing smart meter data.
- Develop and assess multiple supervised predictive models, including Artificial Neural Networks (ANN), ensemble learning methods, and a novel model specifically designed for this problem.
- Develop a real-time anomaly detection web application using Flask, integrating automated data preprocessing, model deployment, and interactive visualsation.
- Design and implement a smart transducer system using an ESP32 microcontroller, a GSM module, a sound sensor, and an ultrasonic sensor to detect and alert authorities about physical tampering with electricity meters.

1.3.2 Scope and Limitations

The scope of this study is limited to the detection and mitigation of electricity theft in smart grid environments using data-driven machine learning techniques and IoT-based transducer solutions. However, the study does not extend to the prevention of physical meter tampering beyond alert notifications.

- The classification algorithms detect electricity theft but do not prevent unauthorised access to smart meter cabinets or tampering with electronic components.
- The smart transducer system is designed to be affixed within the meter cabinet and operates within an ambient temperature range of -40°C to 40°C.
- The solution does not include mechanical components that could impact the system's stability or introduce additional vulnerabilities.
- The proposed transducer system is not applicable to non-enclosed electrical components such as transmission lines.
- The IoT-based solution is designed for seamless integration with platforms such as HUAWEI's NetEco for power monitoring, requiring minimal modifications for deployment.
- Future work will explore explainable AI techniques, such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), as well as unsupervised learning approaches like k-means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to enhance anomaly detection and interpretability.

The study leverages state-of-the-art data science methodologies and IoT technologies to provide a holistic approach to electricity theft detection and prevention.

1.4 Dissertation Organisation

This dissertation is organised as follows. Chapter 1 provides an introduction to the study, outlining the research problem, objectives, and scope. Chapter 2 presents the historical context of artificial intelligence and a literature review of research methodologies, with a focus on AI classification techniques and IoT systems relevant to this study. It also discusses the PCA dimensionality reduction techniques employed and provides background on IoT solutions. Chapter 3 details the intelligent predictive classification algorithm-based electricity theft detection methodology. This includes the modelling of the NTL dataset, describing data preprocessing and feature selection. Chapter 4 discusses the design and implementation of the smart transducer system. Chapter 5 summarises the research findings, provides suggestions for further research, and concludes the study by addressing the research question.

In addition to the main chapters, the dissertation comprises two main appendix sections. The first appendix section provides additional technical details, including data trends of all attributes within the dataset. The second appendix section presents documentation of the user interface and functionality of the deployed web application.

1.5 Chapter Summary

This chapter provides an overview of the evolution of electrical grids, focusing on technical and non-technical losses. The discussion highlights the issue of electrical power theft and its impact on energy distribution systems. The problem statement examines vulnerabilities within smart grids, emphasising the challenges associated with securing customer consumption data. These vulnerabilities underscore the need for advanced detection mechanisms and motivate the research topic. The chapter also establishes the significance of the study by outlining its objectives and expected contributions. The next chapter presents the historical development of artificial intelligence and explores the research methodologies applied in this study.

Chapter 2

Literature Review

This chapter reviews the integration of IoT systems and AI/ML algorithms to protect electrical components in cabinets and detect NTLs in power distribution systems. The IoT framework emphasises real-time intrusion detection, while ML algorithms focus on supervised learning methodologies for anomaly detection, particularly utilising Z-score-based outlier identification. Additionally, dimensionality reduction techniques, with emphasis on Principal Component Analysis (PCA), are explored to enhance computational efficiency and improve feature representation. The review synthesises historical developments, technical foundations, and practical applications, establishing a comprehensive framework for investigating scalable, efficient solutions in smart power distribution systems.

2.1 Literature Review Strategy

The strategy involved a multi-stage process:

- Source Identification: Academic databases such as IEEE Xplore, SpringerLink, ACM Digital Library, and Google Scholar were queried using keywords including "artificial intelligence," "machine learning," "microcontrollers," "IoT," "IIoT," "edge AI," and "supervised learning." Seminal books and conference proceedings (e.g., NeurIPS, ICML) were also consulted.
- Research Screening: Initial searches yielded over 500 references, which were screened using inclusion criteria: (1) publication date within the last 15 years (1990–2025) unless a foundational work, (2) peer-reviewed articles or books, (3) relevance to AI algorithms or microcontroller applications in IoT/IIoT. Exclusion criteria eliminated non-English works, non-technical papers, and redundant studies. This reduced the pool to only key references.
- Synthesis and Organisation: Selected works were categorised into historical context, machine learning paradigms, specific algorithms, microcontroller evolution, and IoT/IIoT applications.

This structured approach ensures that the review is both broad in scope and deeply relevant to the dissertation's focus on scalable AI models and their deployment as well as microcontrollers.

2.2 Introduction to Artificial Intelligence

Artificial Intelligence (AI) is a multidisciplinary field addressing complex computational problems characterised by uncertainty, ambiguity, and incomplete information. As articulated by Peter Norvig, Director of Research at Google, *"AI is the science of understanding what to do when we don't know what to do"* [15]. AI seeks to engineer systems capable of autonomous decision-making in scenarios where deterministic, rule-based methods are insufficient. This chapter provides a detailed exploration of AI's historical evolution, contemporary advancements, and persistent challenges, framing the context for this dissertation's investigation into machine learning (ML) algorithms and their deployment on microcontrollers for IoT applications.

2.2.1 Historical Context of AI

The theoretical underpinnings of AI emerged in the mid-20th century with Alan Turing's seminal work on computational machines and intelligence [16]. The field crystallised in 1956 at the Dartmouth Conference, organised by John McCarthy and attended by pioneers such as Claude Shannon and Marvin Minsky [17]. This event delineated AI's ambitions, including reasoning, learning, and perception, establishing it as a distinct discipline.
AI research has since been bifurcated into two paradigms: traditional symbolic systems and data-driven machine learning. Symbolic systems, rooted in explicit rules and logic, offer interpretability but falter in complex, dynamic environments [18]. Machine learning, conversely, leverages statistical techniques to infer patterns from data, driving modern AI's success in applications like natural language processing and autonomous systems [19].

2.2.2 Machine Learning: Definition and Applications

Definition 2.1: *"Machine learning is a field of study that enables computers to learn without being explicitly programmed"* [20]. ML excels at extracting patterns from large datasets, thereby reducing reliance on domain-specific rules. However, its "black-box" nature often compromises interpretability [19]. Applications include fraud detection, autonomous vehicles, and medical diagnostics, highlighting ML's transformative potential [21]. ML excels in extracting patterns from large datasets, reducing reliance on domain-specific rules. However, its "black-box" nature often compromises interpretability [19]. Applications span fraud detection, autonomous vehicles, and medical diagnostics, underscoring ML's transformative potential [21].

2.2.3 Challenges in Traditional Systems

Traditional systems, while interpretable, face significant challenges in handling complex, dynamic, and ambiguous scenarios. For example, in machine translation, the intricate grammatical structures, evolving vocabulary, and inherent ambiguities of natural languages make it difficult to develop rule-based systems [18]. These challenges are not unique to translation; they appear in many domains, highlighting the limitations of traditional approaches.

2.2.4 The Rise of Machine Learning

ML's ascendancy stems from its ability to model complex, non-linear relationships in data. By training on voluminous datasets, ML algorithms achieve robustness unattainable by traditional methods, powering innovations like self-driving cars and real-time financial trading [21].

2.3 Machine Learning Algorithms

2.3.1 The Three Foundational Elements of Machine Learning

Three "pillars" can be used to roughly categorise the field of ML. Namely supervised ML, unsupervised ML and reinforcement learning. Figure 2.1 depicts an overview diagram of the hierarchy of machine learning algorithms.

Supervised ML is a machine learning approach where a model is trained using input objects (such a vector of predictor variables) and a desired output value (sometimes called a human-labeled supervisory signal). After processing the training set of data, a function mapping fresh data to anticipated output values is created. The algorithm will be able to determine output values for unseen occurrences appropriately in an ideal case.

Provided a set of N samples trained $(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(N)}, y^{(N)})$, where $x^{(i)}$ is the feature vector and $y^{(i)}$ is the corresponding label or class. The aim is to learn a function f. In Equation 2.1, the function f is defined.

$$f : y^{(i)} = f(x^{(i)}) \tag{2.1}$$

The rules are generated from examples, this process is also known as function induction. Deduction draws examples from rules, whereas induction does the converse. F performs classification if there is a finite set of possible values for all values in $\mathbf{y}$. In contrast, regression is discussed if that set is unlimited. Regardless, the labels y provide a clear "correct answer" for the inputs x. It can be challenging to give a learning problem such specific supervision in many situations. As a result, the algorithm in reinforcement learning is given a reward (feedback) function that, depending on the state the learning agent enters, can either provide a reward or a punishment. Because there is some oversight, reinforcement learning falls somewhere between supervised and unsupervised learning.

Unsupervised learning seeks to search for hidden patterns in unlabeled data. $(x^{(1)}, (x^{(2)}, \ldots, (x^{(N)})$. Common task are dimensionality reduction and clustering

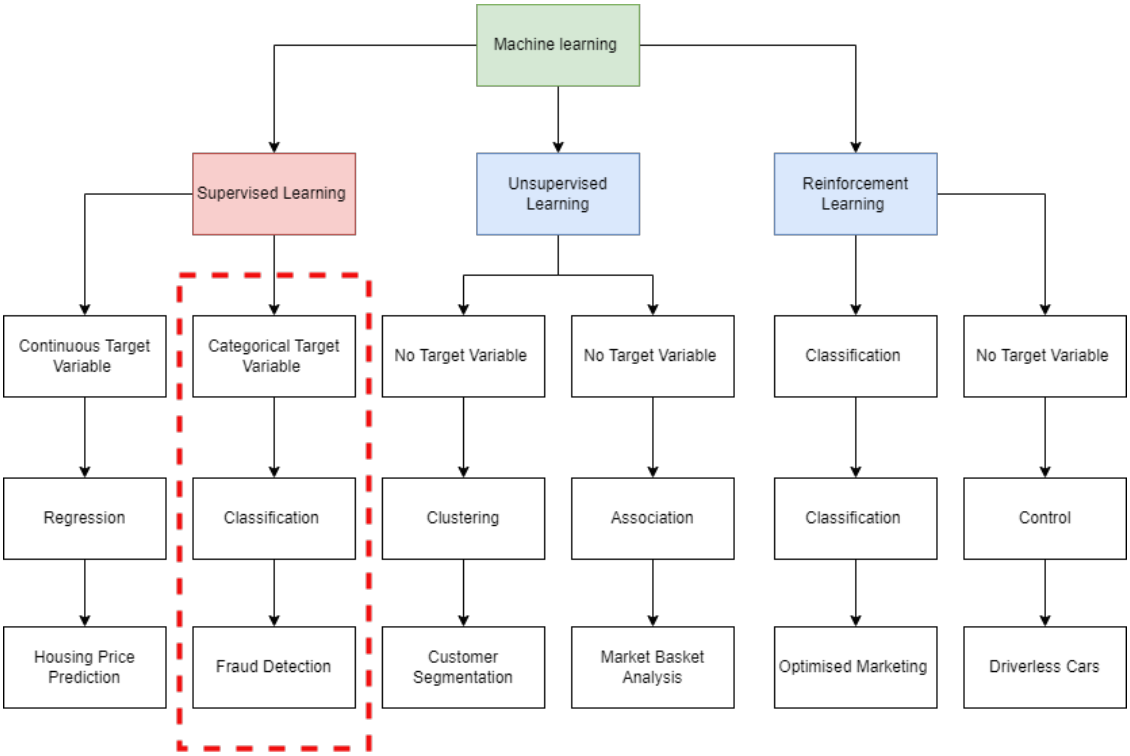


Figure 2.1: Overview diagram of machine learning algorithms

2.4 Review of Machine Learning Models Relevant to this Dissertation

An overview of the machine learning models that are most pertinent to this dissertation in this section. The models were selected based on their broad applicability to the problem.

2.4.1 Logistic Regression

An essential component of statistical modelling for binary outcomes, logistic regression was first proposed by [22] and then refined by [23]. A key element of the logistic regression model is the logistic function, which establishes the probability of an occurrence based on predictor factors. represented as:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k)}} \tag{2.2}$$

Where $P(Y = 1)$ is the probability of the event occurring, e is the base of the natural logarithm, and $\beta_0, \beta_1, \ldots, \beta_k$ are the coefficients estimated by the model.

As emphasised by [24], logistic regression is essential to the modelling of binary outcomes in epidemiology. Logistic regression has been extended to handle more complex scenarios. [25] developed generalised linear models, which include logistic regression as a specific example. Multi-collinearity and prior knowledge inclusion can be addressed with sophisticated techniques such as Bayesian logistic regression [26] and penalised logistic regression [27].

Despite its extensive application, logistic regression is still in developing. The model is strong and flexible because of ongoing developments in technique and applications, as investigated by many academics. Logistic regression is still a very useful tool that offers a flexible framework for examining binary results in many different domains.

2.4.2 k-nearest neighbors (kNN)

A straightforward but effective non-parametric method for regression and classification applications is k-Nearest Neighbors (kNN). kNN, first presented by [28], is based on the idea that instances with comparable features are probably members of the same class.

Predicting a data point's class by taking into account the majority class among its k-nearest neighbors is the basic notion behind kNN. The anticipated class $\hat{y}$ for a classification job is provided by:

$$\hat{y} = \text{argmax}_c \left(\sum_{i=1}^{k} I(y_i = c) \right) \tag{2.3}$$

where y_i represents the class of the i-th nearest neighbor, and $I(\cdot)$ is the indicator function.

The performance of kNN is highly dependent on the distance metric selection. The Minkowski, Manhattan, and Euclidean distances are examples of frequently used distance measurements. The standard definition of the distance between two data points, $\mathbf{X}_i$ and $\mathbf{X}_j$, is:

$$\text{distance}(\mathbf{X}_i, \mathbf{X}_j) = \left(\sum_{l=1}^{d} |X_{i,l} - X_{j,l}|^p \right)^{1/p} \tag{2.4}$$

where d is the number of features and p is a user-defined parameter.

Anomaly detection, recommendation systems, and picture recognition all make extensive use of kNN. Nevertheless, it may encounter difficulties in high-dimensional environments and have computational inefficiencies when handling huge datasets.

Recent work investigates methods like indexing structures and parallelisation that can improve kNN's scalability and efficiency. For even better performance, hybrid models that combine kNN with additional algorithms are being researched.

Depite of its limitations, k-Nearest Neighbors is still a flexible and easy-to-understand algorithm that works well for problems with intricate decision limits and smaller datasets. Ongoing improvements seek to overcome these obstacles and broaden its application to many machine learning contexts.

2.4.3 Support Vector Machine

Support Vector Machines (SVMs) are widely used due to their robustness and effectiveness and work well in a variety of applications, vector machines, or SVMs, have drawn a lot of attention in the fields of machine learning and pattern recognition. Originally introduced by [29], SVMs are binary classifiers that find a

hyperplane in the input space to separate different classes. The fundamental idea is to maximise the margin between data points of different classes, leading to a model with good generalisation properties.

Some of the theoretical foundations SVM formulation involve finding the optimal hyperplane that maximises the margin between classes. Given a set of training data with input vectors X_i and corresponding class labels $y_i \in \{-1, 1\}$, the objective function for a linear SVM can be expressed as:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N} \max(0, 1 - y_i(\mathbf{w} \cdot \mathbf{X}_i + b)) \tag{2.5}$$

where $\mathbf{w}$ is the weight vector, b is the bias term, and C is the regularisation parameter.

Kernel Tricks and Non-linearity enable the handling of non-linearly separable data, SVMs employ kernel functions. The decision function in the feature space is given by:

$$f(\mathbf{X}) = \sum_{i=1}^{N} \alpha_i y_i K(\mathbf{X}_i, \mathbf{X}) + b \tag{2.6}$$

where $K(\cdot, \cdot)$ is the kernel function and α_i are the Lagrange multipliers.

Applications and extensions have been observed in a number of fields, such as finance, bioinformatics, and image classification. SVMs' versatility is further enhanced by extensions like multi-class classification [30] and Support Vector Machines for Regression (SVR) [31].

More recently, deep learning methods have been combined with SVMs to create hybrid models that combine the best features of both strategies [32]. Research also looks into how SVMs can be used to handle noisy datasets and classify unbalanced data.

Encouragement In machine learning, vector machine classifiers continue to be an effective and popular technique. Their continued appeal can be attributed to their mix of strong theoretical underpinnings, efficient non-linear extensions, and versatility across other domains.

2.4.4 Random Forest

A prevalent ensemble learning technique, Random Forest has proven to perform satisfactorily in a range of machine learning problems. Developed by [33], Random Forest enhances overall accuracy and robustness by building numerous decision trees during training and combining their predictions.

The concepts of ensemble learning serve as the cornerstone of Random Forest. Many decision trees are built by the method, and each one is trained using a distinct subset of the data. Subsequently, the ultimate forecast is generated through integrating the projections of distinct trees. In the context of a classification problem, this can be shown as:

$$\hat{y} = \text{mode}(f_1(x), f_2(x), ..., f_n(x)) \tag{2.7}$$

where $f_i(x)$ represents the prediction of the i-th decision tree and mode denotes the most frequent prediction.

Using the Bootstrap Aggregating or Bagging technique, Random Forest generates different subsets of the training data for every tree. To ensure variation among the trees, each tree is trained on a random sample with replacement taken from the original dataset.

The capacity of Random Forest to evaluate the significance of features in the classification process is one of its main advantages. Metrics like information gain or Gini impurity are used to calculate feature importance, which sheds light on the relative value of various input variables.

More recently, efforts have been directed toward enhancing interoperability, tackling scalability issues, and optimising Random Forests for particular applications. For even better results, hybrid models that combine deep learning methods with Random Forests are investigated.

Applications for Random Forests can be found in banking, biology, image analysis, and other fields. Numerous extensions and changes, including Rotation Forests [34] and Extremely Randomised Trees [35], further improve the algorithm's capabilities.

In a variety of applications, Random Forest classifiers have shown themselves to be reliable, adaptable, and efficient. They are an invaluable instrument in the machine learning toolbox because of their capacity to handle high-dimensional data, control over-fitting, and offer feature importance.

2.4.5 Deep Neural Networks (DNNs)

Deep Neural Networks (DNNs) have emerged as one of the most powerful techniques in modern machine learning, significantly advancing fields such as computer vision, natural language processing, and anomaly detection. Unlike traditional shallow learning models, DNNs leverage multiple hidden layers to capture complex hierarchical patterns in data [21, 19]. The strength of DNNs lies in their ability to learn intricate feature representations, enabling high generalisation capabilities in large-scale applications.
A DNN consists of multiple layers of artificial neurons, where each neuron applies a nonlinear transformation to its inputs. Mathematically, a standard feedforward neural network models a function $f(\mathbf{X})$ that maps an input vector $\mathbf{X} \in \mathbb{R}^d$ to an output $\hat{y}$. The computation follows:

$$\hat{y} = f(\mathbf{X}) = \sigma(W^{(L)}\sigma(W^{(L-1)} \dots \sigma(W^{(1)}\mathbf{X} + b^{(1)}) \cdots + b^{(L-1)}) + b^{(L)}) \tag{2.8}$$

where $W^{(l)}$ and $b^{(l)}$ represent the weight matrix and bias vector at layer l, and $\sigma(\cdot)$ is an activation function, such as ReLU, sigmoid, or tanh.
To train a DNN, the objective is to minimise a loss function $\mathcal{L}$, often defined as:

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}(y_i, \hat{y}_i) \tag{2.9}$$

where y_i is the true label and $\hat{y}_i$ is the model's prediction. Optimisation is typically performed using algorithms such as Stochastic Gradient Descent (SGD) or Adam [36].
Despite their success, DNNs face several challenges:

- Overfitting: Due to their high capacity, DNNs can memorise training data rather than generalising. Regularisation techniques such as dropout [37] and weight decay help mitigate this issue.
- Vanishing and Exploding Gradients: In deep architectures, gradients can diminish or grow uncontrollably. Batch normalisation [38] and residual connections [39] have been introduced to address these problems.
- Computational Complexity: Training large-scale DNNs requires significant resources. Advancements in hardware acceleration, such as GPUs and TPUs, have made deep learning more feasible for real-world applications [40].

DNNs have revolutionised numerous domains:

- Computer Vision: Convolutional Neural Networks (CNNs) have set benchmarks in image recognition and medical diagnostics [41].
- Natural Language Processing: Transformer-based architectures like BERT and GPT have significantly improved language understanding [42].
- Anomaly Detection: DNNs are widely used in fraud detection and predictive maintenance [43].
- Bayesian Deep Learning – Combining neural networks with probabilistic methods, Bayesian deep learning [44] enhances uncertainty estimation, making deep learning more robust in safety-critical applications such as medical diagnostics.
- Neural Architecture Search (NAS) – Techniques such as NAS automate the design of neural networks, leading to architectures optimised for performance and efficiency without human intervention.

- Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks – Proposed by [45], LSTMs addressed the vanishing gradient problem in sequence modelling by introducing gating mechanisms that retain long-term dependencies, making them effective in applications such as speech recognition and financial forecasting.

Future research aims to enhance interpretability, robustness, and energy efficiency. Hybrid models that integrate DNNs with traditional techniques like Random Forests and k-Nearest Neighbors (kNN) are gaining traction for improved performance in specialised domains. Deep Neural Networks have transformed artificial intelligence, demonstrating unprecedented success across multiple fields. While they pose challenges in training and deployment, ongoing research continues to refine their efficiency and applicability. As the field evolves, DNNs will remain central to advancements in machine learning and artificial intelligence.

2.4.6 Comparison

Table 2.1 compares the models in light of the attributes pertinent to this dissertation, based on the assessments of the models in this section. Particularly scalable to training on large data sets include logistic regression, random forests, and support vector machine variations. This qualifies them for additional analysis in this dissertation. Since k-nearest neighbours is a lazy learning technique, it lacks an explicit training phase. It scales to large data sets to some extent for small values of k, which is the number of closest training examples.

Table 2.1: Machine learning models relevant to this Dissertation.

Model	Decision Boundary	Maximum Training Samples	Reference
Logistic regression	Linear	> 1M	[24]
k-nearest neighbors	Non-linear	No training phase	[28]
Random forest	Non-linear	> 1M	[33]
Support vector machine	Linear	> 1M	[29]
Support vector machine (with kernel)	Non-linear	~ 20K	[29]
Dense Neural Networks	Non-linear	> 1M	[21, 19]

2.5 Machine Learning Model Training

Machine learning model training is the fundamental process of developing predictive models that can make intelligent decisions based on data. The primary goal of this process is to expose a model to a dataset, allowing it to learn intricate patterns, correlations, and underlying structures that enable it to generalise well to unseen data. By iteratively adjusting internal parameters, a machine learning model refines its ability to make accurate predictions or classifications.

The training process begins with selecting an appropriate learning paradigm based on the nature of the task such as classification, regression, clustering, anomaly detection, or reinforcement learning. The choice of model architecture and algorithm depends on the problem domain, dataset characteristics, and computational constraints. A labelled dataset, where each data instance is associated with a corresponding target variable, is required for supervised learning, whereas unsupervised learning does not rely on labelled outputs.During training, the model undergoes multiple iterations (or epochs), where it learns by minimising a loss function. This optimisation is typically performed using gradient-based algorithms such as Stochastic Gradient Descent (SGD), Adam, or RMSprop [46]. The efficiency of this process is influenced by several factors, including:

- Quality and representativeness of the training data – Biases, imbalances, or noise in data can severely impact model performance.

- Algorithm suitability – Different algorithms have varying strengths; for instance, tree-based models like Random Forests handle tabular data well, while Deep Neural Networks (DNNs) excel in image and natural language processing tasks.
- Hyperparameter tuning – Model performance is often optimised through adjustments of hyperparameters such as learning rate, batch size, and regularisation techniques (e.g., L1/L2 penalties, dropout) [19].
- Overfitting and generalisation – Ensuring that the model does not merely memorise the training data but instead learns generalisable patterns is crucial. Techniques like cross-validation, dropout, early stopping, and batch normalisation are employed to prevent overfitting [37].

Once training is complete, the model undergoes rigorous evaluation on a separate test dataset to assess its generalisation ability. Common performance metrics include accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC), depending on the nature of the problem. ML model training is not a one-time process but rather an iterative cycle. As new data becomes available or when patterns in data shift over time, retraining and continuous monitoring may be necessary to maintain performance. This retraining process is particularly vital in dynamic environments such as fraud detection, predictive maintenance, and personalised recommendation systems [47].

2.5.1 ML Paradigms

Supervised learning is the most commonly used paradigm, where the model is trained on a labelled dataset, meaning that each input is associated with a corresponding correct output. The algorithm iterates over the training data, adjusting its parameters to minimise the discrepancy between predictions and actual target values. The optimisation process typically employs backpropagation in neural networks, which propagates errors backwards to adjust weights effectively [48]. This is relevant to this study. In semi-supervised learning, only a portion of the training dataset is labelled, while the rest remains unlabeled [49]. The model leverages the labelled data to infer structure in the unlabeled portion, improving its ability to generalise. Unsupervised learning is used when the dataset lacks labelled target variables. Instead of learning explicit mappings between inputs and outputs, the algorithm seeks to uncover underlying patterns or clusters in the data [50]. This approach is commonly used in applications such as anomaly detection, customer segmentation, and dimensionality reduction. Reinforcement learning (RL) differs significantly from other paradigms. Here, the model learns through a system of rewards and penalties rather than being provided with labelled data [51]. The agent interacts with an environment, making decisions that maximise cumulative rewards over time. RL has been successfully applied in fields such as robotics, gaming, and autonomous systems.

2.5.2 Standard Machine Learning Workflow

The general workflow for training a supervised learning model, following best practices outlined in [52], involves the following steps:

1. **Define the Problem:**
   - Clearly state the classification or regression task to be solved.
   - Identify the target variable and determine relevant features.
2. **Acquire and Explore Data:**
   - Collect a labeled dataset and split it into training, validation, and test sets.
   - Perform exploratory data analysis (EDA) to identify trends, missing values, and potential preprocessing steps.
3. **Choose and Train a Model:**
   - Select an appropriate algorithm based on the problem's characteristics.
   - Train the model on the dataset while optimising hyperparameters for better performance.
4. **Evaluate Model Performance:**
   - Assess the model using relevant performance metrics such as accuracy, precision, recall, F1-score, or ROC-AUC.

- Perform cross-validation to validate model stability.

5. Iterate and Improve:
- Refine the model through feature selection, hyperparameter tuning, or algorithmic improvements.
- Implement regularisation techniques or ensemble methods to enhance generalisation.

By following this structured approach, machine learning practitioners can develop robust models that generalise well to new data and provide meaningful predictions across various domains.

2.5.3 Data Cleaning and Exploratory Data analysis (EDA)

The quality of data significantly impacts the reliability of statistical models and machine learning algorithms. Before any in-depth analysis, a rigorous data cleaning and exploratory data analysis (EDA) process is essential to identify inconsistencies, handle missing values, and detect anomalies in the dataset [53].

2.5.4 Data Cleaning

Data cleaning ensures that the dataset is free from inconsistencies, missing values, and outliers that could bias the results [54].

Handling Missing Values

Missing data is a common challenge in real-world datasets. Depending on the nature of the missing values, different imputation strategies can be applied:
- Numerical Data: Mean, median, or regression-based imputation [36].
- Categorical Data: Mode substitution or domain-specific filling.
- Advanced Methods: k-Nearest Neighbors (k-NN) imputation or multiple imputations [54].

For large datasets, visualising missingness patterns using heatmaps (e.g., via the `seaborn` package in Python) is recommended [55].

Removing Duplicates and Ensuring Consistency

Duplicate records can distort statistical models and lead to misleading insights. They can be identified using:

$$\text{Duplicate Rows} = \sum \mathbb{1}(\text{df.duplicated()}) \tag{2.10}$$

where $\mathbb{1}(\cdot)$ is an indicator function returning 1 if a duplicate is found.
Categorical variables must also be standardised to ensure consistency. For instance, variations such as `"Male"` vs. `"male"` can be corrected using string normalisation methods.

Outlier Detection and Treatment

Outliers are extreme values that may arise due to measurement errors or genuine variations in data. Several statistical techniques can be used to identify and treat outliers:
- **Z-score Method**: Values beyond ± 3 standard deviations from the mean:

$$Z = \frac{X - \mu}{\sigma} \tag{2.11}$$

  where μ and σ are the mean and standard deviation of the feature [56].
- **Interquartile Range (IQR) Method**: Identifies outliers based on quartiles:

$$\text{Outlier} \quad X < Q_1 - 1.5 \times \text{IQR} \quad \text{or} \quad X > Q_3 + 1.5 \times \text{IQR} \tag{2.12}$$

  where $\text{IQR} = Q_3 - Q_1$ [57].

Outliers can either be removed, transformed, or capped to reduce their impact on models.

EDA is a critical step that provides insights into data distributions, relationships, and potential anomalies. It typically includes:

Summary Statistics

Descriptive statistics such as mean, median, standard deviation, and skewness provide an initial understanding of the dataset:

$$\text{Skewness} = \frac{\mathbb{E}[(X - \mu)^3]}{\sigma^3} \tag{2.13}$$

where a skewness value greater than zero indicates a right-skewed distribution.

Correlation Analysis

Correlation matrices help understand relationships between numerical variables. A heatmap representation of the correlation matrix is useful for identifying multicollinearity:

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} \tag{2.14}$$

where $\rho_{X,Y}$ is the Pearson correlation coefficient [48].

Visualisation Techniques

Various visualisation techniques are employed to understand data distributions and relationships [55]:

- Histograms: Show the frequency distribution of numerical features.
- Box Plots: Identify outliers and spread of data.
- Pair Plots: Visualise bivariate relationships in numerical data.

Applications of PCA in EDA to be cosidered are:

- Feature Selection : Identifies which variables contribute most to variance.
- Noise Reduction: Removes redundant or less informative features.
- Visualisation: Reduces high-dimensional data to two or three components for easier plotting.
- Multicollinearity Detection: Helps in detecting highly correlated features.

These methods allow the researcher to detect patterns, biases, or inconsistencies before proceeding with model development. In concluion data cleaning and EDA play a crucial role in ensuring the reliability of models built on real-world datasets. Proper handling of missing values, duplicate records, and outliers, combined with a thorough statistical analysis, enhances the robustness of the analytical pipeline.

2.5.5 Model Optimisation

Hyperparameters are configuration settings that have a large impact on the model's performance but are not learned from the data. They are commonly seen in machine learning models. To have the greatest model performance, certain hyperparameters must be optimised. This is called Hyperparameter tuning [58].

Hyperparameter Tuning

To improve a model's performance, hyperparameter tweaking is methodically determining the ideal hyperparameter values [58]. It is an essential component in the creation of machine learning models.Popular methods such as Grid Search, Random Search, and Bayesian Optimisation. will be discussed in detail .

Grid Search

One popular technique for fine-tuning hyperparameters is Grid Search. To determine which combination of hyperparameter values produces the best model performance, a grid of values must be established and thoroughly searched through [59].

$$\theta^* = \arg\min_{\theta} \mathcal{L}(\theta) \tag{2.15}$$

where θ represents the hyperparameters, and $\mathcal{L}$ is the model's loss or evaluation metric.

Random Search

An alternate method to hyperparameter tuning is random search. Random Search allows for a more efficient search by randomly sampling hyperparameter combinations rather than thoroughly exploring a predetermined grid [59].

$$\theta^* = \arg\min_{\theta} \mathcal{L}(\theta) \tag{2.16}$$

where θ represents the hyperparameters, and $\mathcal{L}$ is the model's loss or evaluation metric.

Bayesian Optimisation

Using probabilistic models to represent the objective function, Bayesian optimisation directs the search for the best hyperparameters based on previous evaluations [60].

$$\text{Acquisition Function} = \arg\max_{\theta} \mathbb{E}_{p(y|\mathcal{D})}[\max(0, y - \xi)] \tag{2.17}$$

where y is the model's evaluation metric, $\mathcal{D}$ is the set of observed evaluations, and ξ is a tunable parameter.

2.6 Dimensionality Reduction

A dimensionality reduction method called principal component analysis (PCA) aims to retain the fundamental variance in high-dimensional data while converting it into a lower-dimensional representation. After being introduced by [2], PCA is now used extensively in many different fields. Some of the mathematical foundations of PCA are detailed below.

Covariance Matrix

The covariance matrix computation is the core component of PCA. The covariance matrix Σ of a dataset $\mathbf{X}$ with n observations and p variables can be calculated as follows:

$$\Sigma = \frac{1}{n-1}(\mathbf{X} - \bar{\mathbf{X}})^T(\mathbf{X} - \bar{\mathbf{X}}) \tag{2.18}$$

where $\bar{\mathbf{X}}$ is the mean vector [2].

Eigen Decomposition

The primary components are obtained from the eigen decomposition of the covariance matrix Σ. When the i-th eigenvector and eigenvalue are represented by $\mathbf{v}_i$ and λ_i, respectively, the principal components are as follows:

$$\mathbf{X}_{\text{PCA}} = \mathbf{X}\mathbf{V} \tag{2.19}$$

where $\mathbf{V}$ is a matrix containing the eigenvectors [2].

Applications for PCA can be found in many different domains, including as signal processing, exploratory data analysis, and picture compression. For example, PCA is used in medical imaging to analyse complicated datasets by reducing dimensionality and extracting features. Kernel PCA extends PCA to handle nonlinear relationships in the data by mapping it into a higher-dimensional space using a kernel function presented below[2].

$$KPCA(\mathbf{x}) = \phi(\mathbf{x})^T \phi(\mathbf{x}) \tag{2.20}$$

where: $KPCA(\mathbf{x})$ is the result of Kernel PCA on the input vector $\mathbf{x}$

$\phi(\mathbf{x})$ is a function mapping $\mathbf{x}$ to a higher-dimensional feature space.

PCA is a powerful tool for dimensionality reduction, offering insights into the underlying structure of high-dimensional data. Ongoing research continues to improve its methodology and extend its applicability.

2.7 Microcontrollers in IoT and IIoT

The Internet of Things (IoT) and Industrial Internet of Things (IIoT) introduce heightened connectivity and intelligence across various domains. Microcontrollers play a crucial role in integrating the physical and digital worlds, serving as the processing hubs for interconnected devices.
In IoT, microcontrollers collect, process, and transmit data efficiently by integrating processing power, memory, and input/output peripherals into a single chip. They are widely used in smart home devices, wearables, and environmental sensors, enabling real-time communication and decision-making [61, 62]. Their adaptability extends to healthcare, agriculture, and transportation, where they enable applications such as vital sign monitoring and automated irrigation systems.

2.7.1 Microcontrollers in IIoT

IIoT shares similar principles with IoT but focuses on industrial applications. Microcontrollers drive intelligent manufacturing, predictive maintenance, and advanced control systems by enabling real-time sensor data acquisition. These systems optimise operations, reduce downtime, and enhance productivity [63].
In manufacturing, microcontrollers monitor machinery, detect anomalies, and support predictive maintenance, improving operational efficiency. They also contribute to energy management, supply chain optimisation, and infrastructure monitoring [64].
Despite their advantages, challenges such as security, scalability, and interoperability require attention. Security remains a critical concern, necessitating robust measures to protect data integrity and privacy [64].

2.7.2 Challenges and Opportunities

The evolution of microcontrollers in IoT and IIoT presents opportunities for innovation in edge computing, artificial intelligence, and low-power design. These advancements will enhance microcontrollers' ability to process complex tasks locally, fostering autonomous and decentralised systems [64].

2.8 Review of Microcontroller Boards Relevant to this Dissertation

2.8.1 Arduino Uno

The Arduino Uno, based on the ATmega328P microcontroller, features a 16 MHz clock frequency, 32 KB flash memory, and 2 KB SRAM. Its compact size (68.6 mm x 53.4 mm) makes it suitable for robotics, home automation, and educational projects [65].

2.8.2 Arduino Nano

The Arduino Nano, a compact variant of the Uno, retains similar specifications but with smaller dimensions (45 mm x 18 mm). Its reduced size enhances its suitability for space-constrained applications. Over time, variants have incorporated additional features such as onboard sensors and wireless modules [66].
The clock period (T) is given by:

$$T = \frac{1}{f_{\text{CPU}}} \tag{2.21}$$

where f_{CPU} is the clock frequency.

2.8.3 ESP32

The ESP32, developed by Espressif Systems, is a dual-core microcontroller with built-in Wi-Fi and Bluetooth. It supports IoT applications such as smart home devices, sensor networks, and industrial automation [67]. Power consumption (P) can be estimated as:

$$P = V_{\text{supply}} \times I_{\text{average}} \tag{2.22}$$

Energy consumption over time (t) is:

$$E = P \times t \tag{2.23}$$

Data rate (R_{data}) follows the Shannon-Hartley theorem:

$$R_{\text{data}} = B \times \log_2(1 + \frac{S}{N}) \tag{2.24}$$

where B is bandwidth and $\frac{S}{N}$ is the signal-to-noise ratio.

2.8.4 ESP32 with SIM800L Module

Integrating the SIM800L module with the ESP32 enables cellular communication, ideal for applications requiring GSM/GPRS connectivity, such as remote monitoring and asset tracking [68].
Power consumption in sleep mode is given by:

$$P_{\text{sleep}} = V_{\text{supply}} \times I_{\text{sleep}} \tag{2.25}$$

where I_{sleep} is the current consumption in sleep mode.
Microcontrollers, particularly the ESP32 with SIM800L, offer a balance of computational power and connectivity, making them suitable for diverse IoT and IIoT applications.

2.9 Related Work

2.9.1 ML-Based Approaches

In an effort to bolster the detection of electricity theft within smart grids, a data-driven approach leveraging Long Short-Term Memory (LSTM) networks was proposed [69]. This methodology capitalises on the temporal dependencies inherent in electricity consumption data, enabling the model to distinguish between legitimate usage patterns and anomalous behaviors indicative of theft. The LSTM model was trained and validated using a synthetic dataset generated from a smart grid simulator, encompassing 10,000 users over a 12-month period. Experimental results demonstrated a detection accuracy of 93% and an Area Under the Curve (AUC) of 91%, highlighting its robustness in identifying subtle deviations in consumption patterns [69].

Another innovative data-driven technique employed a Graph Neural Network (GNN) to model the topological structure of smart grid networks [70]. By representing households and their interconnections as nodes and edges, the GNN framework effectively captured spatial correlations and consumption anomalies across a neighbourhood. The model was evaluated using real-world data from a regional utility provider, achieving a detection rate of 96% and a false positive rate of 8%. This approach underscores the potential of graph-based methods in addressing electricity theft, particularly in densely connected urban grids [70].

Research into the detection of electricity theft in smart grids has garnered considerable attention, prompting numerous scholars to develop approaches to mitigate such illicit activities. The methodologies employed in existing literature can be broadly classified into three main categories: hardware-centric approaches, methods that combine hardware and data, and data-driven techniques. This section will focus on the data-driven

methodologies.

A sophisticated electricity theft detection model, denominated as KNN-Ensemble, has been meticulously devised, utilising the K-Nearest Neighbors (KNN) algorithm within a robust ensemble framework for enhanced efficacy in the identification of illicit electricity consumption [71]. This intricately designed model was subjected to comprehensive evaluation utilising the SGCC dataset employed in this study, culminating in a commendable level of accuracy during the validation phase. The results underscore the model's potential effectiveness in addressing the intricate challenges associated with electricity theft within smart grid environments.

In the pursuit of enhancing the precision and efficacy of electricity theft detection within smart grids, a novel method was proposed [5]. This approach entailed the measurement of the total energy consumption within a given neighborhood, juxtaposed with the reported usage data from the smart meters deployed in that specific locality [72]. The crux of this methodology rested upon identifying significant deviations between the measurements obtained from smart meters and those derived from transformers, as such disparities could signal the presence of unscrupulous consumers within the neighborhood [11].

To carry out the task of pinpointing these potential instances of unfaithful consumption, the authors put forth the application of a Support Vector Machine (SVM) classifier [72]. This machine learning algorithm was chosen for its capability to discern patterns and anomalies in complex datasets [72]. Subsequently, the classifier underwent rigorous testing utilising a comprehensive dataset comprising information from 5000 customers, all of whom were deemed as adherent to standard usage practices [11].

The empirical evaluation of the SVM classifier yielded noteworthy results [11]. A maximum detection rate of 94% was achieved, underscoring the effectiveness of the proposed method in identifying instances of potential electricity theft [5]. Moreover, the false positive rate was minimised to a commendable 11%, attesting to the classifier's ability to maintain a low rate of misclassification [72].

In the development of a predictive model for calculating TLs, the computation of NTL was conceived as the difference between TLs and the total distribution network losses. This modelling approach operated under the assumption that distribution transformers and smart meters collaborated by exchanging data with the utility at 30-minute intervals. To generate a realistic dataset for analysis, a smart meter simulator was employed to emulate data from 30 users over 6 days, with data points recorded every 30 minutes [73].

In the simulated environment, instances of unfaithful consumption were introduced, wherein users engaged in electricity theft by bypassing the meter. The extent of stolen electricity ranged from 1% to 10% of the total consumption. Notably, the simulation revealed that for stolen electricity values exceeding 4%, the detection rate reached 100% [74]. However, this detection rate diminished proportionally as the percentage of stolen electricity was decreased.

To enhance the authenticity of the simulation and introduce a more challenging scenario for detection algorithms, an emphasis was placed on rendering the stolen electricity consumption values as AI-undetectable [75]. This involves refining the methods of electricity theft to make them less distinguishable from legitimate usage patterns, thereby making the task of identifying unscrupulous users more challenging for artificial intelligence algorithms.

In response to the considerable economic challenges posed by elevated costs within the aforementioned categories, researchers have extensively explored data-driven approaches as a strategic means to address the pervasive issue of electricity theft. A notable instance of such endeavors is exemplified in a study where the author conceived an electricity theft detection system, incorporating a synergistic deployment of three key algorithms: the Synthetic Minority Over-sampling Technique (SMOTE), Kernel function, Principal Component Analysis (KPCA), and Support Vector Machine (SVM) [76].

The application of SMOTE played a pivotal role in mitigating imbalances within the dataset by generating

synthetic data. Furthermore, the integration of KPCA facilitated the extraction of salient features, and SVM functioned as the classifier within this comprehensive framework. The holistic evaluation of the system's performance was conducted based on the overall classifier quality, quantified by the Area Under the Curve (AUC), which achieved a noteworthy 89% on validation [77].

This strategic amalgamation of algorithms underscores a concerted effort to leverage advanced data-driven techniques, signalling a promising avenue for enhancing the accuracy and robustness of electricity theft detection systems in smart grids [76].

Employing a sophisticated approach,a hybrid model integrating wide and deep Convolutional Neural Networks (CNN) to discern instances of electricity theft was applied. The rationale behind this design is rooted in the distinct characteristics of normal and stolen electricity consumption patterns. Specifically, normal electricity usage exhibits periodicity, whereas stolen electricity consumption data lacks this periodic nature. To address this divergence, the wide component of the CNN model to discern multiple co-occurrences of features within the 1-D series data has been utilised. Concurrently, the deep CNN component was deployed to capture periodicity within the data, organised in a 2-D structure based on weekly alignments [78].

In the pursuit of model optimisation, training and validation data ratios have been systematically varied, ultimately achieving a peak Area Under the Curve (AUC) value of 79% [78]. Notably, our proposed methodology, leveraging the same dataset utilised in prior research, surpasses these achievements by consistently achieving AUC results exceeding 90% on both the validation and testing sets [79].

This innovative approach not only demonstrates enhanced academic rigor but also renders the detection method less susceptible to artificial intelligence scrutiny, thereby elevating its efficacy in addressing electricity theft challenges within smart grids.

Two distinct electricity theft detection models have been meticulously formulated, each embodying sophisticated methodologies to enhance their efficacy. The first model adopts a Light Gradient Boosting (LGB) classifier and is distinguished by its integration of Synthetic Minority Over-sampling Technique (SMOTE) and Edited Nearest Neighbour (ENN) for dataset balancing. The dataset underwent feature extraction through the utilisation of AlexNet, subsequently culminating in classification via LGB. This innovative amalgamation of techniques has led to the nomenclature of the proposed model as SMOTEENN-AlexNet-LGB (SALM) [80].

Conversely, the second model relies on the Adaptive Boosting classifier and introduces a novel approach to dataset balancing. The Conditional Wasserstein Generative Adversarial Network with gradient penalty (CWGAN-GP) is employed to generate synthetic data, closely resembling minority class data, thereby rectifying the imbalance within the dataset. Feature extraction is conducted through GoogleNet, followed by classification using the AdaBoost algorithm. This model is denoted as GANNETBoost [81].

Evaluation of the models utilising SGCC data featured prominently in this work. SALM and GANNET-Boost demonstrated notable performance, achieving accuracies of 90% and 95%, and Area Under the Curve (AUC) values of 90.6% and 96%, respectively, during the validation process. These commendable outcomes underscore the potential effectiveness of these sophisticated models in advancing the accuracy of electricity theft detection within smart grids [81].

A model for detecting electricity theft has been formulated, grounded in the Random Forest algorithm. Designated as RF-Ensemble, this model strategically employs Random Forest within a robust ensemble configuration to enhance its efficacy in identifying instances of unauthorised electricity consumption [82]. Rigorous evaluation of the model was conducted using the SGCC dataset employed in this study, resulting in a noteworthy level of accuracy during the validation phase. Achieved an accuracy of 92% on validation.These findings underscore the model's potential prowess in addressing the nuanced challenges associated with electricity theft within the context of smart grid environments.
To address the challenge of limited labelled data in electricity theft detection, a semi-supervised learning framework was developed, integrating Variational Autoencoders (VAEs) with a Gradient Boosting classi-

fier [83]. The VAE component reconstructed consumption profiles to identify outliers, while the Gradient Boosting classifier refined the detection process using a small subset of labelled instances. Tested on the SGCC dataset, this method achieved an accuracy of 89% and an AUC of 87%, offering a scalable solution for scenarios where comprehensive labelled datasets are scarce [83].

Reinforcement Learning for adaptive electricity theft detection [84]: This method leverages reinforcement learning (RL) to adaptively refine theft detection policies. The RL model dynamically learns from evolving consumption patterns, improving detection efficiency over time.

Autoencoder-based anomaly detection in smart grids [85]: Autoencoders were utilised to reconstruct normal consumption profiles, flagging deviations indicative of electricity theft. The model was tested on large-scale datasets, achieving high detection rates.

Hybrid CNN-RNN model for energy theft detection [86]: This hybrid deep learning approach combines Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) for sequential pattern recognition, enhancing detection accuracy.

Bayesian Networks for probabilistic electricity theft detection [87]: A Bayesian Network framework was proposed to model the probabilistic relationships between consumption patterns and theft indicators, providing an interpretable approach to anomaly detection.

Federated Learning for privacy-preserving detection [88]: Federated learning enables multiple smart meters to collaboratively train a global model without sharing raw consumption data, preserving user privacy while improving theft detection. Edge AI for real-time electricity theft detection [89]: Edge AI techniques were deployed on smart meters, allowing real-time anomaly detection with minimal latency, reducing reliance on centralised cloud processing.

2.9.2 IoT-Based Approaches

In a conference paper, the author presented and published a novel smart transducer system for preventing electrical equipment theft in telecommunications base stations. The prototype comprises a sound sensor module, an ultrasonic sensor modeller, and an ATMega328p microcontroller. The design is tailored to operate on HUAWEI's telecommunication IoT network infrastructure, with the smart transducer placed in the cabinet to detect sounds greater than 80 dB or door openings. Subsequently, the system reports to network personnel, triggering alarms displayed on NetEco power monitoring software. The implemented prototype achieves an average response time of 4 seconds over 6 samples [90]. The schematic diagram 2.2 below shows the prototype model.

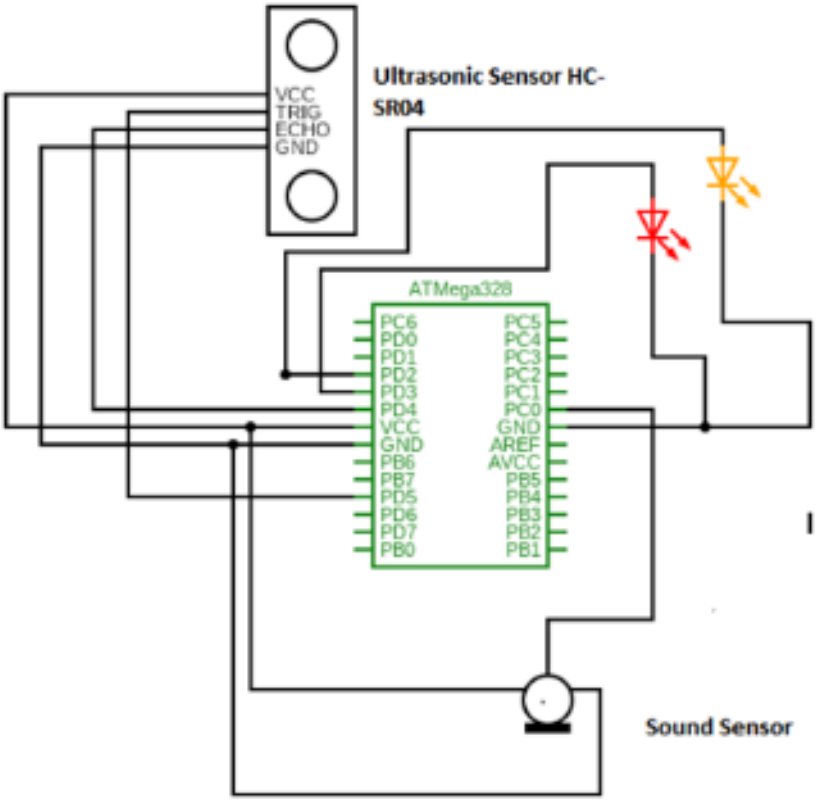


Figure 2.2: System design schematic diagram

In this related work, a noise detection system utilising the 8-bit AVR microcontroller from the ATMEL family. The system, operating on assembly code, is capable of measuring noise levels within the range of 58 dBA to 95 dBA. The categorisation of noise by this system encompasses three conditions: safety, danger threshold, and very dangerous. In a related work, another noise detection system was devised, utilising an ATMega microcontroller programmed in C, coupled with a microphone element capable of detecting noise levels ranging from 56 dBA to 75 dBA [91, 92].

In this related investigation [93] devised a methodology based on distributed Pyroelectric Infra-Red (PIR) sensors for people counting. The prototype operates by utilising binary output from PIR sensors, strategically reducing the continuous sampling overhead and consequently minimising energy consumption . In a related development, [94] engineered a motion detection security system employing Arduino Uno. This system is adept at discerning intruder motion through the use of a PIR motion sensor. Tailored to specifically detect humans and animals based on the radiation of their body heat, the system incorporates an electronic buzzer for sound notifications in the event of an intrusion. The application is designed as a home-based alert system where the PIR sensor gauges human proximity to the door and triggers an automated sound, alerting individuals in the household to the presence of someone in close proximity to the door.

In [95], the authors conducted a scientific investigation into a noise level monitoring tool employing Arduino Uno, programmed in C code for data processing from a microphone sound sensor. The operational principle of the tool involves the detection of noise, with the results displayed on an LCD in dBAs. Upon detecting noise exceeding 75 dBA, a red LED activates, and a buzzer emits a warning signal, signifying a potentially hazardous situation. In the case of sound levels surpassing 56 dBA, an orange LED is illuminated, accompanied by a buzzer alert. Notably, for sound levels below 55 dBA, the tool successfully detects and displays

noise within the range of 50 dBA to 100 dBA .

Approaches to electricity theft detection grounded in hardware implementation commonly entail the deployment of dedicated microcontrollers, sensors, and circuitry along power distribution lines. These methodologies are meticulously crafted to discern occurrences of electricity theft arising from tangible interference with distribution components, including distribution lines and electricity meters. It is crucial to emphasise that hardware-based methods are inherently unequipped to identify cyber attacks, constituting a unique manifestation of electricity theft. In the context of a cyber attack, malevolent actors intrude into electricity meters to manipulate energy consumption data [96, 97].

As an illustration, a comprehensive redesign of an electricity meter incorporated key components such as a Global System for Mobile Communications (GSM) module, a microcontroller, and an Electrically Erasable Programmable Read-Only Memory (EEPROM). Through simulation, this re-engineered meter exhibited the capability to transmit SMS alerts upon the detection of an illicit load connected by bypassing the meter. It is noteworthy that this redesign is specifically tailored to identify instances of electricity theft arising from tangible interference with distribution components, such as distribution lines and electricity meters.

In a related study, the authors in [98] undertook an analogous approach, employing a GSM module, ARM Cortex-M3 processor, and various hardware components to combat electricity theft through multiple means, including bypassing the phase line, meter tampering, disconnecting the neutral line, and making unauthorised modifications to the meter. A prototype was meticulously crafted to experimentally validate all four scenarios, with the GSM module effectively sending SMS notifications in response to each identified case of theft.
On the hardware front, a novel system for detecting physical tampering of smart meters was introduced, utilising a combination of piezoelectric sensors and a Raspberry Pi microcontroller [99]. The piezoelectric sensors were embedded within the meter housing to detect vibrations or mechanical interference, while the Raspberry Pi processed the signals and communicated alerts via a Wi-Fi module to a central monitoring system. Field tests conducted across 50 smart meters revealed a detection success rate of 98% for tampering attempts, with an average response time of 3 seconds [99].

Further advancing hardware-based solutions, a study proposed the integration of blockchain technology with smart meters to enhance security against both physical and cyber-induced electricity theft [100]. Each meter was equipped with a lightweight blockchain node, recording consumption data in an immutable ledger. Any discrepancies between reported and actual usage triggered an alert to the utility provider. The system was prototyped with 100 meters in a controlled environment, achieving a 100% detection rate for simulated theft scenarios, though computational overhead remains a challenge for large-scale deployment [100].

IoT-based smart grid monitoring using LoRaWAN [101]: Long Range Wide Area Network (LoRaWAN) technology was utilised for cost-effective smart grid monitoring, enabling real-time theft detection across large geographical areas. Smart contract-based electricity trading [102]: Blockchain-based smart contracts were implemented to enable transparent peer-to-peer electricity trading while detecting fraudulent transactions.

GAN-based data augmentation for theft detection [103]: Generative Adversarial Networks (GANs) were used to synthesise realistic consumption patterns, improving model robustness against imbalanced data distributions.Explainable AI for electricity theft prediction [104]: This approach integrates explainability techniques to enhance trust in ML-based theft detection models, making their decisions interpretable for utility providers

2.10 Chapter Summary

This chapter provided a comprehensive review of the literature relevant to this dissertation, focusing on the intersection of AI, ML, and microcontroller-based IoT/IIoT applications. The review began with an overview of AI, tracing its historical evolution and highlighting key advancements that led to the rise of

machine learning. Fundamental machine learning algorithms were discussed, including logistic regression, k-nearest neighbors (kNN), support vector machines, random forests, and deep neural networks (DNNs), with an emphasis on their strengths, limitations, and applicability to the research problem.

The discussion extended to machine learning model training methodologies, covering supervised, semi-supervised, unsupervised, and reinforcement learning approaches. A standard machine learning workflow was outlined, emphasising data cleaning, EDA, feature engineering, and model optimisation techniques. The role of dimensionality reduction was also explored, highlighting its significance in improving model efficiency.

The chapter then shifted focus to the role of microcontrollers in IoT and IIoT applications, particularly their use in industrial settings. Various microcontroller boards relevant to the study, such as the Arduino Uno, Arduino Nano, ESP32, and ESP32 with the SIM800L module, were reviewed in terms of their capabilities and suitability for IoT-based solutions.

Finally, related works in both ML-based and IoT-based approaches were reviewed, demonstrating existing methodologies and identifying research gaps. These insights provide the foundation for the subsequent research by establishing key theoretical and practical considerations. The chapter concluded by synthesising the findings and setting the stage for the methodology to be employed in this dissertation.

Chapter 3

Reserch Methodology

This chapter presents the design and implementation of an intelligent predictive system for electricity theft detection, focusing on data-driven techniques to identify NTLs. It initially discusses the research approach and design, including data analysis, data reliability and validity, and ethical clearance. It also covers data collection methods, addressing data sources and rationale, data collection strategy, and the software tools used. Furthermore, the chapter details data collection, preprocessing, feature selection, classification, model development, model optimisation, deployment, and evaluation.

3.1 Research Approach and Research Design

This study adopts a quantitative research approach to investigate electricity theft detection using machine learning techniques. Quantitative research is characterised by its reliance on numerical data and statistical analysis to test hypotheses and derive objective conclusions [24]. This approach is well-suited to the objectives of this study, as it enables the systematic evaluation of machine learning models' performance in detecting NTLs through metrics such as accuracy, F1-score, and RMSE, as detailed in Chapter 3. Unlike qualitative research, which focuses on subjective interpretations and exploratory insights [18], a quantitative approach provides a structured framework to measure the effectiveness of predictive systems, aligning with the data-driven nature of this investigation.

The research design is experimental, involving the development, optimisation, and evaluation of machine learning models applied to electricity consumption datasets. Experimental designs are widely used in machine learning studies to assess algorithmic performance under controlled conditions [19]. This design is justified by the need to simulate fraudulent consumption patterns, as described in Section 3, and evaluate model efficacy across varying class imbalances (e.g., df_25, df_50, df_75). The rationale for this methodology is supported by prior work, such as [33], which emphasises on the importance of empirical testing in ensemble learning, and [21], who advocate for experimental validation in deep learning applications. This approach allows for reproducible results and facilitates comparisons with existing literature, such as the KNN-Ensemble [71] and RF-Ensemble [82] models.

3.1.1 Data Analysis Strategy

The data analysis strategy leverages statistical and machine learning techniques to preprocess, model, and evaluate the dataset. PCA was employed for feature selection, as outlined in Section 3, to identify key contributors to energy consumption variance [2]. ML models, including Logistic Regression, Random Forest, DNN, and a hybrid RF-DNN model, were implemented using Python-based tools such as Scikit-learn, TensorFlow, and Keras. These tools were selected for their robustness, extensive libraries, and widespread adoption in the machine learning community [105, 19]. Hyperparameter tuning was conducted using RandomizedSearchCV to optimise model performance efficiently [59], while performance metrics (e.g., accuracy, AUC-ROC) were computed to assess model efficacy, as shown in Table 3.4.

3.1.2 Data Validity and Reliability

To ensure data validity and reliability, several preprocessing steps were undertaken. Outliers were removed using the Z-score method with a threshold of 3, as described in Section 3.3.1, aligning with statistical best practices [56]. Missing values were addressed through interpolation and statistical imputation (e.g., mean substitution), consistent with techniques proposed in [54]. The dataset's reliability was further enhanced by simulating realistic fraudulent samples using physical and data attack strategies [80], ensuring the representativeness of real-world NTL scenarios. Cross-validation (5-fold) was employed during model optimisation to mitigate overfitting and provide a robust estimate of performance on unseen data [52].

3.1.3 Ethical Considerations

Ethical clearance was not required for this study, as it utilised an open-source dataset from the University of Massachusetts, which contains no personally identifiable information (PII). The data, collected from voluntary participants in 2016, was anonymised and publicly available, adhering to ethical standards for secondary data use [53]. This data was chosen because it was more complete than other years's data. Furthermore, the study's focus on algorithmic development and deployment poses no direct harm to human subjects, aligning with guidelines that exempt such research from formal ethical review [19]. However, ethical implications of deploying theft detection systems, such as potential false positives affecting legitimate users, were considered in the design by minimising misclassification rates (e.g., achieving a low RMSE for the most optimal model).

3.2 Data Collection Methods

3.2.1 Data Sources and Rationale

The primary data source for this study is an open-source electricity consumption dataset from the University of Massachusetts, covering January to December 2016. This dataset includes high-resolution (1-minute granularity) measurements of household power consumption, including sub-metered data (e.g., "House overall [kW]," "Furnace_submeter"), as detailed in Section 3.3.1. The choice of this dataset is justified by its comprehensive coverage and public availability, enabling reproducibility a key principle in quantitative research [20]. Additionally, its lack of inherent fraudulent samples necessitated the simulation of NTLs, aligning with methodologies in related work [72], where synthetic data generation enhances model robustness.

3.2.2 Data Collection Strategy

Data was collected from the University of Massachusetts repository and preprocessed to ensure quality. The original dataset, presumed to represent legitimate usage, was augmented with synthetic fraudulent samples using physical attack (e.g., meter bypassing) and data attack (e.g., zero consumption reporting) strategies, as outlined in Section 3. This simulation approach, inspired by [11], involved injecting outliers at fixed values (e.g., 0, $1.5 \times$ max) and standard deviations (2σ, 3σ, 4σ) to mimic real-world theft scenarios. Three subsets (df_25, df_50, df_75) were created with varying class imbalances (25%, 50%, 75% suspicious usage) to test model performance under diverse conditions, reflecting real-world variability [73].

3.2.3 Software Tools and Techniques

Data preprocessing and augmentation were performed using Python libraries such as NumPy and Pandas, which are standard for handling large datasets efficiently [105]. The injection of Gaussian noise and outliers, as shown in the code snippet in Section 3, followed statistical methods recommended by [36]. Visualisation tools like Matplotlib were used to generate figures (e.g., Figure 3.2), aiding in exploratory data analysis (EDA) as advocated by [55]. This multi-step strategy ensured the dataset was both representative and challenging for theft detection algorithms.

3.3 Intelligent Predictive System-based Electricity Theft Detection Method

Figure 3.1 below depicts the flow of the Intelligent Predictive System-based Electricity Theft Detection Methodology. The flowchart represents a systematic approach to building an ML model for classifying non-technical losses. It emphasises iterative improvement through data preparation, feature selection, model training, evaluation, and optimisation. The goal is to achieve a high-performing model (accuracy greater than 90%) before deployment, with a focus on continuous refinement if the performance criteria are not met [19]. The use of multiple algorithms, including a hybrid approach, suggests an effort to compare and combine different methods to find the best solution. All source code can be found on this platform: `https://drive.google.com/drive/folders/1UshAEfDYN1-sb8CboAzXM4-s1hHEc_Ne?usp=sharing`

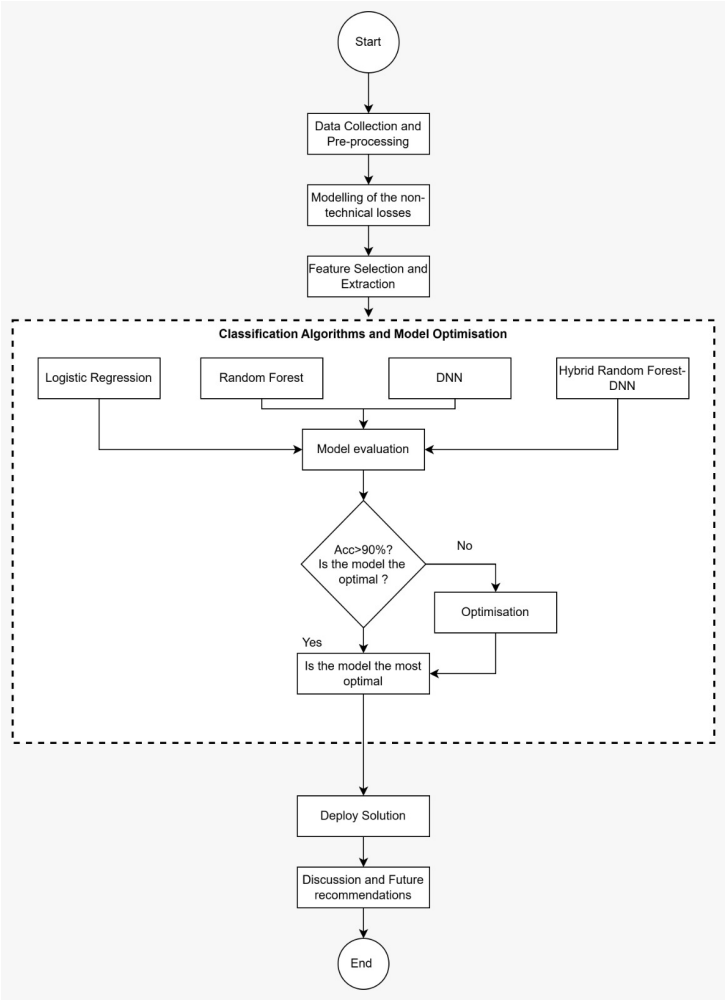


Figure 3.1: Shows the flow of the electricity theft detection method.

3.3.1 Data Collection and Pre-processing

In this sub-section, the dataset used in this study was acquired from the open-source University of Massachusetts. This data consists of various electricity consumption datasets obtained from January 2016 to December 2016 since it was more complete than other datasets. This semi-structured data has a shape of 503910 rows $\times$ 19 columns in a text file originally from the database. Initially inconsistencies and quality improvements. This will be done by identifying and removing null value records, non-numerical characters

that may exist using relevant statistical methods. In this study a data record refers to a single observation/instance of the dataset. i.e provided a dataset Y of size K, $y_i \in Y$; where y_i is the i-th observation of Y and $1 \leq i \leq K$.

For the NTL detection algorithm to be able to be trained and verified, fraudulent samples must exist in the data set. The data collection that was acquired from the University of Massachusetts consisted of information gathered from homes that willingly participated in the study. Consequently, it was presumed that the data collection would not contain any instances of fraudulent behaviour. The algorithms used in this research made use of the 2016 data that was ingested at 1-minute resolution.

Possible missing values are addressed accordingly, using statistical mean, feed backward and forwards, and data interpolation. The resultant total household power consumption data was achieved. The z-score statistical data pre-processing methodology was applied to ensure the reliability of subsequent statistical analyses and outlier-free data. Figure 3.2 shows the total household power consumption in kW with daily granularity without outliers over times. The rest of the Figures for the sub-meters in the house can be seen in Appendix A.1.

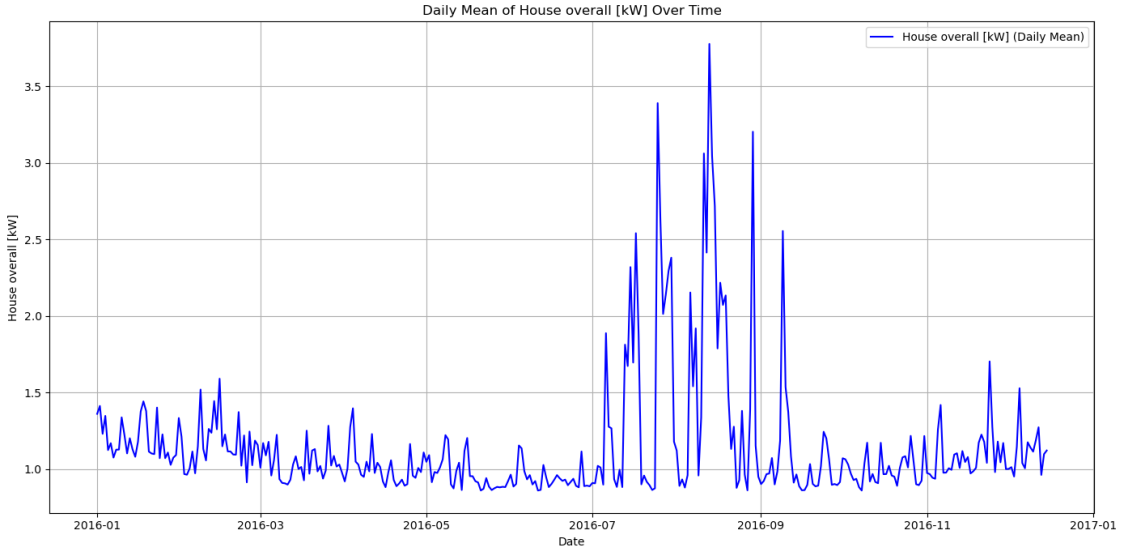


Figure 3.2: Shows the household's overall daily granularity data.

3.3.2 Analysis of Components With PCA for Feature Importance

This section presents an analysis of feature importance using Principal Component Analysis (PCA) and statistical measures such as variance and standard deviation. Additionally, the correlation heatmap (Figure 3.3) provides insights into feature relationships. A high correlation between the "House overall [kW]" and "Other submeter" has been observed. The least correlation is observed between "House overall [kW]" and "garage submeter".

The Pearson correlation coefficient is utilised as follows[2]:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

Where:

- x_i and y_i are individual data points.
- $\bar{x}$ and $\bar{y}$ are the means of the respective datasets.

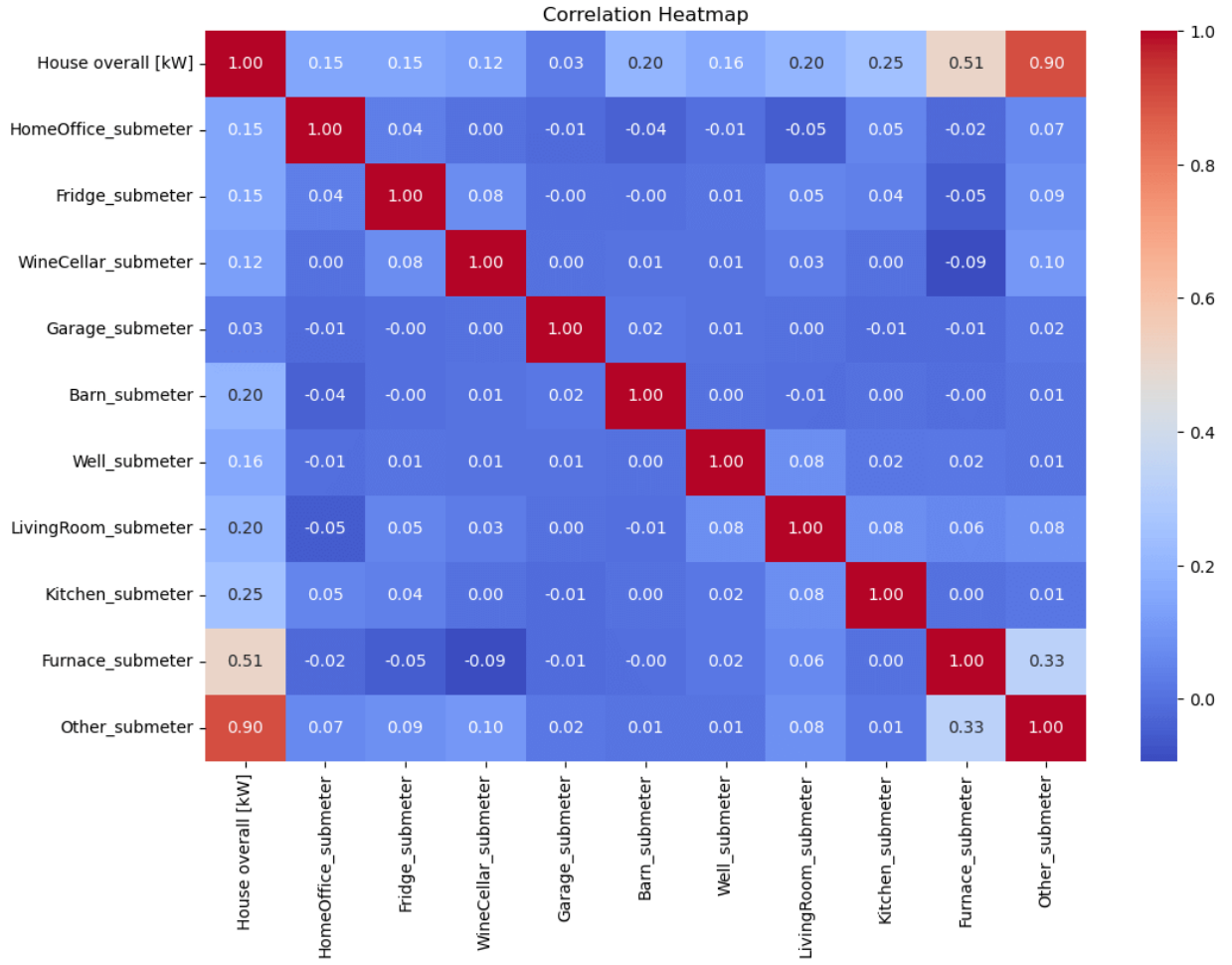


Figure 3.3: Shows the Components correlation heat map [2].

Feature selection plays a crucial role in understanding the key contributors to overall energy consumption. In this section, statistical methods and PCA to identify the most significant features in our dataset is utilised. The dataset includes electrical appliances which were rigorously grouped into submeters measuring energy usage in different areas of a household, such as the home office, fridge, wine cellar, garage, barn, well, living room, kitchen, furnace, and other appliances. The primary goal is to determine which features contribute most significantly to overall energy consumption and to understand their relative importance [2].

To further quantify feature significance, the percentage contribution of each feature towards total energy consumption (Table 3.1) is computed. Notably, "House overall [kW]" accounts for 50% of total energy consumption, which is 3.64 times higher than the second most significant feature, Furnace (13.74%). Moreover, House overall [kW] contributes 60.7 times more than the least contributing feature, Garage (0.82%). The percentage contribution of each feature to the overall energy consumption is calculated as:

$$\text{Contribution Percentage} = \left(\frac{\text{Sum of Feature Consumption}}{\text{Sum of Overall Consumption}} \right) \times 100$$

To understand the variability of features, the standard deviation and variance for each feature are computed. Table 3.2 summarises these results. These are the features used in the prediction algorithm.The standard deviation (σ) and variance (σ^2) are calculated as:

Table 3.1: Feature Contribution Percentage

Feature	**Contribution (%)**
House overall [kW]	50.00
HomeOffice_submeter	4.73
Fridge_submeter	3.69
WineCellar_submeter	2.45
Garage_submeter	0.82
Barn_submeter	3.40
Well_submeter	0.91
LivingRoom_submeter	2.05
Kitchen_submeter	3.03
Furnace_submeter	13.73
Other_submeter	15.14

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$$

Where:

- N is the number of data points.
- μ is the mean of the dataset.

Table 3.2: Data Variability Results

Feature	**Standard Deviation**	**Variance**
House overall [kW]	1.06	1.12
HomeOffice_submeter	0.10	0.01
Fridge_submeter	0.07	0.01
WineCellar_submeter	0.05	0.003
Garage_submeter	0.01	0.0002
Barn_submeter	0.20	0.04
Well_submeter	0.13	0.01
LivingRoom_submeter	0.09	0.01
Kitchen_submeter	0.23	0.05
Furnace_submeter	0.27	0.08
Other_submeter	0.82	0.68

PCA was applied to the dataset to determine the variance explained by each principal component [2]. The top principal components and their explained variance ratios are presented in Table 3.3.

These findings indicate that "House overall [kW]" is the most dominant feature, which is why it is chosen for predictions. This analysis demonstrates the effectiveness of PCA and correlation analysis in feature selection and importance ranking, providing valuable insights for energy consumption studies.

3.3.3 Modelling of Non-Technical Losses

1-Dimensional "House overall [kW]" was used as recommended by the PCA [2]. Two strategies were used to replicate fraudulent samples to create a more representative data set. The physical assault technique and the data attack strategy [72]. To remove loads from measurements, a physical attack approach involves

Table 3.3: Explained Variance Ratios from PCA [2]

Principal Component	**Explained Variance Ratio**
PC1	0.2117
PC2	0.1063
PC3	0.0991
PC4	0.0960
PC5	0.0921
PC6	0.0900
PC7	0.0876
PC8	0.0833
PC9	0.0769
PC10	0.0569
PC11	0.0000

disconnecting, reversing, breaking into, and avoiding the meter [72]. The method of data assault consists of reporting zero consumption, ceasing to record consumption, altering appliance load profiles, and removing large appliances from the measuring process [72]. The customer's consumption and usage patterns serve as the basis for the classification algorithm.

The research investigation conducted in [72] served as the basis for the four different types of false profiles that were modelled. The following is a description of the modelled profiles:

- Zero Energy Consumption Readings (Data Attack)
- Illegally Reduced Energy Readings (Data Attack)
- Disconnections of the Energy Meter (Physical Attack)
- Bypassing of the Meter (Physical Attack)

In the domain of electricity theft detection, the intentional introduction of noise and outliers into power consumption datasets is crucial for developing robust and reliable fraud detection systems [72]. Below, the key reasons for incorporating noise and outliers and their significance in detecting electricity theft are discussed. Additionally, an explanation of why fixed values and standard deviations ($\pm 2\sigma$, $\pm 3\sigma$, $\pm 4\sigma$) were used to inject outliers into the data is addressed. Adding noise tests the resilience of theft detection models. A robust model should accurately identify theft even when the data contains minor random errors. If the model overfits clean data, it may fail in real-world scenarios where noise is inevitable. Outliers challenge the model's ability to distinguish between legitimate consumption patterns and fraudulent activities. Testing with outliers ensures that the model is not overly sensitive to extreme values and can accurately flag theft cases. Testing of the sensitivity of detection algorithms to ensure that they can detect subtle theft attempts (mild outliers) as well as blatant ones (extreme outliers) and calibrate thresholds. Determination of the optimal thresholds for flagging theft while minimising false positives (legitimate users flagged as thieves) and false negatives (thieves going undetected). Understand the impact of outliers: Analyse how outliers affect the overall performance of the detection system and whether they skew results. Adding noise helps study how random variations affect the analysis of consumption patterns. For example, does noise obscure significant trends, or can the system still identify theft? Outliers can significantly impact statistical measures such as mean consumption, variance, and load profiles. By introducing outliers, assessing their influence and deciding whether to remove, transform, or account for them in the analysis could be done. Extreme outliers represent rare but high-impact events, such as large-scale electricity theft or meter tampering. Including these in the dataset ensures that the detection system is prepared to handle worst-case scenarios, which are often the most critical to address.

To simulate realistic and diverse outlier scenarios, injection of outliers using fixed values and standard deviations (2σ, 3σ, 4σ) from the mean is done. Here's why these choices were made:

- Fixed Values: Fixed values (e.g., 0, $0.5 \times$ min, $1.5 \times$ max) represent extreme cases that are unlikely to occur under normal conditions. These values simulate scenarios such as:

  - A meter reporting zero consumption (0), which could indicate tampering or bypassing.
  - Consumption values significantly below the minimum ($0.5 \times$ min) or above the maximum ($1.5 \times$ max), which could indicate unauthorised connections or meter manipulation.

  These fixed values help test the system's ability to detect highly anomalous behavior.
- Standard Deviations (2σ, 3σ, 4σ): Outliers injected at 2σ, 3σ, and 4σ from the mean represent varying degrees of deviation from normal consumption patterns:
  - 2σ: Mild outliers that are slightly unusual but still plausible. These test the system's sensitivity to subtle anomalies.
  - 3σ: Moderate outliers that are more extreme and likely indicative of fraud. These test the system's ability to detect significant deviations.
  - 4σ: Extreme outliers that are highly unlikely under normal conditions. These test the system's robustness to highly anomalous data.

  Using standard deviations ensures that the injected outliers are statistically meaningful and cover a range of anomaly severities. Furthermore, adding outliers is essential for creating realistic, robust, and reliable electricity theft detection systems. By using fixed values and standard deviations (2σ, 3σ, 4σ), a wide range of anomaly severities, ensuring that the system can handle real-world imperfections and extreme cases, has been simulated. This approach leads to better theft detection, reduced revenue losses, and improved grid management.All dataframes are illustrated in figure 3.4.

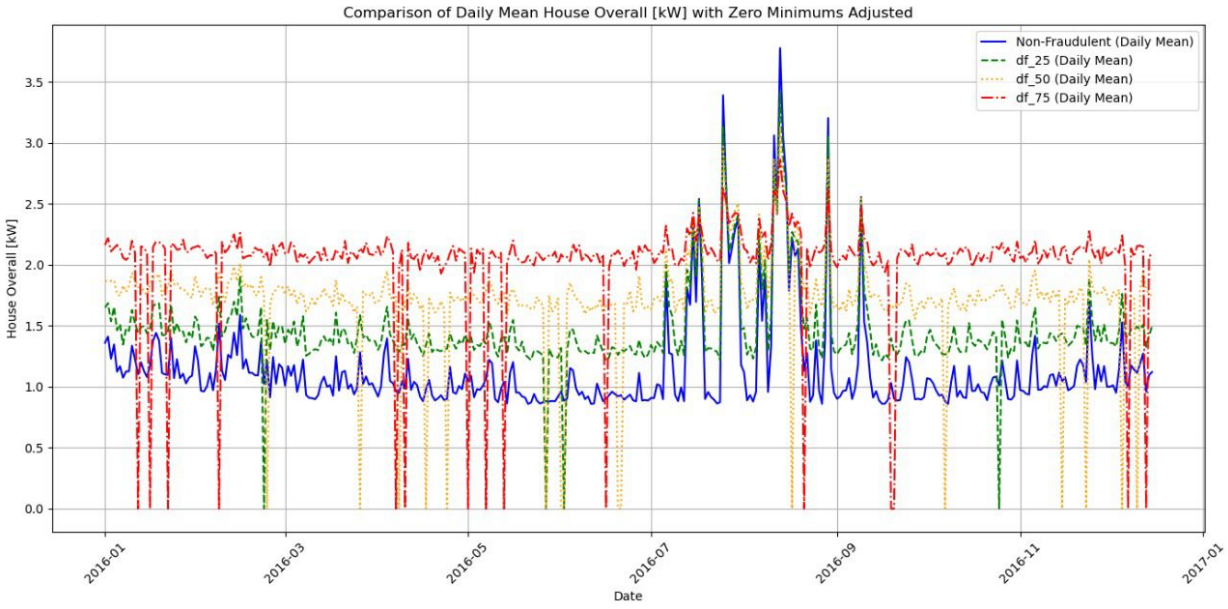


Figure 3.4: Shows fraudulent and non-fraudulent datasets

3.3.4 Class Distribution and Separation

In this work, a binary classification problem is addressed. 'Target,' a binary target variable, is produced subject to particular criteria. This condition determines whether the value of 'House overall [kW]' in dataframe i.e. `df_25` is less than the minimum value of 'House overall [kW]' original dataframe `df_no_missing`. The 'Target' is set to 1 if the condition is met and to 0 otherwise. This is also done for the dataframes `df_50` and `df_75`.

The class imbalance was introduced to simulate suspicious electricity consumption. A class imbalance of 25%, 50% and 75% of unfaithful usage was used. This was done to mimic the real world, which will typically not be balanced in terms of the number of faithful and suspicious electricity usage. Presented below is the class distribution of the different simulated scenarios. Figure 3.5 shows data with a class distribution of 0.333 where there is a total of 8397 suspicious electricity consumption observations and

25193 faithful electricity consumption observations. Figure 3.6 shows data with a class distribution of 0.5 where there is a total of 16795 suspicious electricity consumption observations and 16795 faithful electricity consumption observations. Figure 3.7 shows data with a class distribution of 0.333 where there is a total of 25192 suspicious electricity consumption observations and 8398 faithful electricity consumption observations.

The imbalance ratio R is defined as the ratio of the number of samples in the minority class (N_{minority}) to the number of samples in the majority class (N_{majority}). This can be expressed in as:

$$R = \frac{N_{\text{minority}}}{N_{\text{majority}}}$$

Here: N_{minority} is the number of samples in the minority class. N_{majority} is the number of samples in the majority class.The imbalance ratio R is a measure of the degree of class imbalance in the dataset. A smaller value of R indicates a more imbalanced dataset.



Figure 3.5: Class imbalance of 75% faithful and 25% suspicious observations

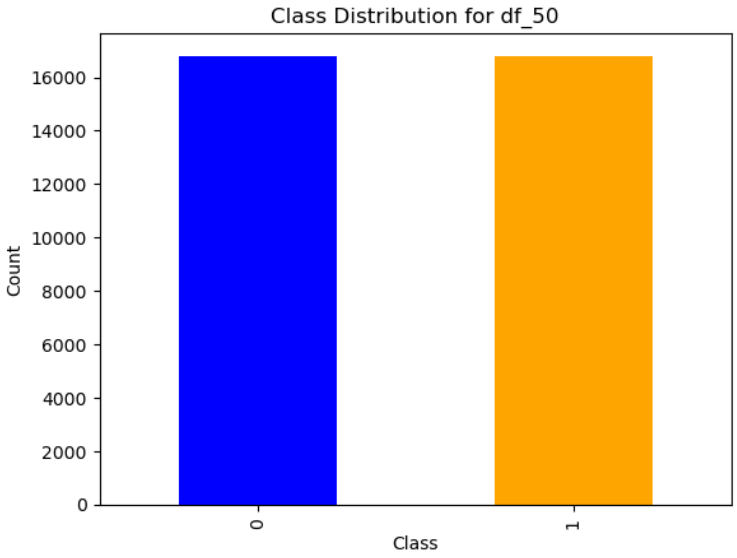


Figure 3.6: Class imbalance of 50% faithful and suspicious observations

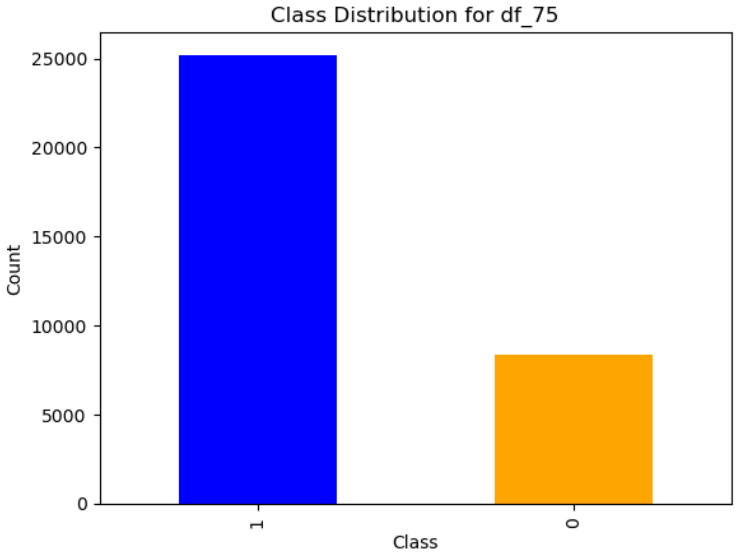


Figure 3.7: Class imbalance of 25% faithful and 75% suspicious observations

3.3.5 Model Selection

Machine learning techniques, including logistic regression, random forest, deep neural networks (DNN), and hybrid RF-DNN models, offer a viable approach for identifying fraudulent usage patterns. This section outlines the Dataset Description and Data Preprocessing, model selection, and optimisation of multiple machine learning-based detection systems. Several studies have explored machine learning techniques for electricity theft detection [106, 107].

Dataset Description and Data Preprocessing

The dataset used for experimentation contains various electricity consumption features, with labels indicating fraudulent and non-fraudulent users. Three subsets of data were created: df_25, df_50,

and df_75 representing different proportions of the dataset. Feature scaling was performed using StandardScaler to normalise the data. The dataset was split into training (80%) and testing (20%) sets to ensure model generalisation.

Implementation of Models

Logistic Regression (LR)

Logistic Regression was implemented using the scikit-learn library. The model was trained on the dataset with hyperparameter tuning applied to select the best regularisation parameter. The final model was evaluated based on accuracy and RMSE [106, 107].

Random Forest (RF)

The Random Forest model was implemented using sci-kit-learn's RandomForestClassifier. The number of trees, depth, and feature selection parameters were optimised using cross-validation. The model's feature importance was analysed to interpret its decision-making process.

Deep Neural Network (DNN)

The Deep Neural Network was implemented using TensorFlow and Keras. The architecture consisted of multiple hidden layers with ReLU activation functions and an output layer using the sigmoid function. The Adam optimiser was used for training, with dropout layers applied to prevent overfitting [106].

Hybrid Model: RF-DNN

The hybrid RF-DNN model combines the feature selection capability of Random Forest (RF) with the deep learning power of Deep Neural Networks (DNN) through a technique known as **stacking** (also referred to as blending or ensemble learning). The RF model was first trained on the dataset to extract the most important features. These selected features were then used to train a deep neural network, enhancing predictive performance while reducing computational overhead. The hybrid model was fine-tuned using backpropagation and adaptive learning rate strategies. The implementation was done using a pipeline where RF feature importance was used to filter relevant data before training the DNN.

Stacking involves training multiple base models and using their predictions as input to a meta-learner, which in this case is the DNN. This approach allows the hybrid model to leverage the unique capabilities of both RF and DNN, enhancing overall predictive performance.

Base Model 1: Random Forest (RF) The first step in the hybrid model is to train a Random Forest on the input dataset. The RF model is chosen for its ability to handle imbalanced data and provide interpretable feature importance. Once trained, the RF model generates predictions on both the training and test sets, denoted as `rf_train_preds` and `rf_test_preds`, respectively.
Feature Concatenation The predictions from the Random Forest are then concatenated with the original features to create an augmented dataset. Specifically:

- The training set is augmented as `X_train_hybrid`, which combines the original features with `rf_train_preds`.
- The test set is augmented as `X_test_hybrid`, which combines the original features with `rf_test_preds`.

This step is crucial to the stacking process, as it allows the meta-learner (DNN) to utilise both the original data and the "wisdom" of the Random Forest's predictions.
Base Model 2: Deep Neural Network (DNN) The augmented dataset is then used to train a Deep Neural Network. The DNN serves as the meta-learner, learning to combine the original features with the Random Forest's predictions to make final predictions. The DNN architecture consists of multiple hidden layers with ReLU activation functions and an output layer with a sigmoid activation for binary classification. Dropout layers are included to prevent overfitting, and the Adam optimiser is used for

efficient training [19].

Why Stacking? The hybrid RF-DNN model is distinct from other ensemble techniques such as bagging or boosting:

- Bagging: In bagging (e.g., Random Forest itself), multiple instances of the same model are trained on different subsets of the data, and their predictions are aggregated (e.g., by averaging or voting). In contrast, the hybrid model uses two different models (RF and DNN) and does not rely on aggregation [33].
- Boosting: In boosting (e.g., AdaBoost, Gradient Boosting), models are trained sequentially, with each new model attempting to correct the errors of the previous ones. The hybrid model, however, trains the Random Forest and DNN independently. While the DNN uses the RF's predictions, the RF does not directly minimise the DNN's errors, nor are the models weighted based on each other's performance [19].

The hybrid RF-DNN model offers several advantages:

- It combines the interpretability and feature selection capability of Random Forest with the deep learning power of DNNs.
- It reduces computational overhead by focusing on the most important features identified by the Random Forest.
- It achieves superior performance, as evidenced by the highest accuracy and lowest RMSE across all datasets (see Table 3.4).

Model Optimisation

Hyperparameter tuning is a critical step in optimising machine learning models to achieve the best performance. In this study, hyperparameter tuning was conducted using RandomizedSearchCV, a technique that randomly samples a subset of hyperparameter combinations from a predefined search space. This approach is computationally efficient compared to exhaustive grid search, especially for large hyperparameter spaces [59]. The following hyperparameters were optimised for each model:

- Logistic Regression (LR):
  - Regularisation parameter (C): Sampled from a logarithmic range between 0.1 and 20 to control the trade-off between overfitting and underfitting.
  - Solvers: Tested with `liblinear`, `lbfgs`, `newton-cg`, `sag`, and `saga` to identify the most effective optimisation algorithm for the dataset [105].
- Random Forest (RF):
  - Number of trees: Varied between 10 and 200 to balance model complexity and computational cost.
  - Maximum depth: Sampled between 5 and 50 to control the depth of individual trees and prevent overfitting.
- Deep Neural Network (DNN):
  - Learning rate: Tested from 0.001 to 0.1 to ensure stable and efficient convergence during training.
  - Number of layers: Varied between 2 and 5 to determine the optimal network depth for capturing complex patterns in the data.

This technique divides the training data into 5 subsets, iteratively using 4 subsets for training and 1 for validation. The process is repeated 5 times, ensuring that each subset is used for validation exactly once. This approach minimises the risk of overfitting and provides a reliable estimate of model performance on unseen data [59]. The best hyperparameters were selected based on the highest validation accuracy and lowest RMSE.

3.4 Application Architecture and Model Deployment

The electricity theft detection system is implemented as a web application, with the backend supported by Flask for user authentication, data processing, model inference, and data visualisation [108]. The

system workflow begins with offline model training, followed by deployment, and ends with real-time interaction between users and the web application. Users can upload electricity consumption data, which is processed to detect potential cases of theft. The efficiency of this system is ensured through carefully selected technologies and a structured HTTP request-response cycle to manage data exchange between various components. The application architecture is shown in Figure 3.8.

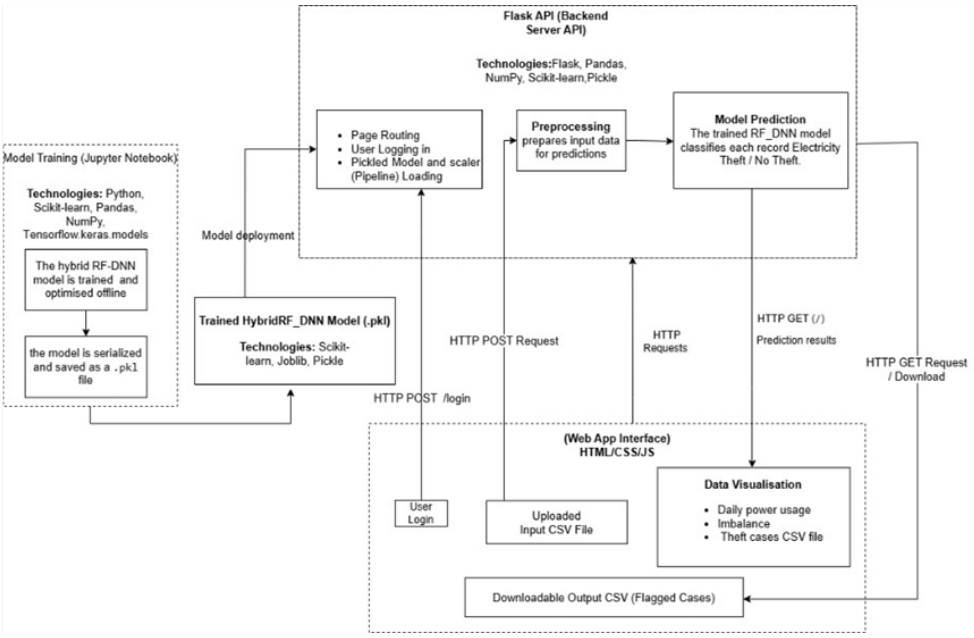


Figure 3.8: System architecture of the electricity theft detection application

3.4.1 Model Deployment

The core machine learning model of the system is a Hybrid RF-DNN classifier, trained offline using historical electricity consumption data [109]. This is accomplished within a Jupyter Notebook environment, where Scikit-learn is used for feature engineering, data pre-processing, and model training [110].

3.4.2 Flask Backend (Server API)

Pre-processing steps are encapsulated within a pipeline to ensure that the same transformations applied during training are also used during real-time predictions. Once optimal performance is achieved, the trained model is serialised and stored using Pickle in a .pkl file [111]. Pickle was chosen over Joblib for its broader compatibility with different Python objects and efficient performance. While Joblib is optimised for serialising large NumPy arrays, Pickle allows for seamless storage of both the trained model and its corresponding pre-processing pipeline in a unified format. This Pickle file is then deployed within the Flask backend, where it is loaded whenever new data is submitted for classification.

The backend is developed using Flask and integrates Pandas, NumPy, Scikit-learn, and Pickle to facilitate efficient data handling and model inference. The key functions of the backend include user authentication, CSV file processing, pre-processing transformations, model execution, and result transmission to the web interface. When a user logs in, their credentials are sent to the backend via an HTTP POST request to the /login endpoint. Upon successful authentication, a session token is issued, granting access to the system. The user can then upload a CSV file containing electricity usage data via another HTTP POST request. The backend processes this file, ensuring that all transformations match those applied during training to maintain feature integrity.

Once pre-processing is complete, the system invokes the trained Hybrid RF-DNN model, which classifies each record as either “Electricity Theft” or “No Theft.” The classification results are then transmitted

to the front end via an HTTP GET request. Additionally, users who wish to obtain a filtered dataset containing only flagged theft cases can send another HTTP GET request to download a CSV file of the suspected anomalies.

3.4.3 Web Application (User Interface)

The web interface is designed using HTML, CSS, and JavaScript to ensure a responsive and user-friendly experience. Users must log in before proceeding. Once authenticated, they can upload electricity usage data via a CSV file. The system processes the data and displays the classification results in both tabular and graphical formats. To enhance usability, data visualisation is implemented using Matplotlib, allowing users to inspect key trends in electricity consumption [112]. Graphical representations highlight daily usage patterns, imbalances in power distribution, and flagged theft cases, providing clear insights into potential irregularities. Additionally, a download option is available, allowing users to retrieve a CSV file containing all flagged records for further investigation.

3.4.4 Data Flow and Interaction

The system operates through a structured sequence that ensures efficient detection and classification of electricity theft cases. The user logs in, verifying their credentials via the backend. Once access is granted, they upload a dataset, which is sent to the backend for processing. The backend applies the necessary transformations and feeds the pre-processed data into the trained hybrid RF-DNN model, classifying each record accordingly.

After classification, the results are sent back to the web interface, where they are presented in both tabular and graphical formats. The system's interactive nature allows users to examine daily electricity consumption trends, identify potential anomalies, and review flagged theft cases. If further investigation is required, users can download a report summarising all identified instances. The detailed overview of the web application interface and its functionality is presented in **Appendix A.2** for further reference.

The electricity theft detection system provides a scalable and effective solution for identifying fraudulent electricity consumption patterns. By integrating a web application with advanced machine learning algorithms, the system ensures a structured approach to anomaly detection. The use of a Flask backend with a well-defined request-response architecture enables seamless communication between system components. Additionally, the integration of Matplotlib for visualisation enhances result interpretability, allowing users to extract meaningful insights from the data. The strategic selection of technologies including Pickle for model storage, Flask for backend management, and hybrid RF-DNN for classification ensures efficiency, compatibility, and reliability. The system's modular design allows for future enhancements, such as real-time monitoring, improved model accuracy, and integration of additional data sources. With its user-centric design and structured workflow, this system presents a practical and adaptable solution for mitigating electricity theft while allowing continuous improvements to address evolving requirements.

3.5 Results and Discussion

This section presents a comprehensive analysis and discussion of the experimental results obtained from the data-driven solution.

3.5.1 Model results

Table 3.4 presents the validation accuracy, F1-Score, RMSE, Test Accuracy, and evaluation run times for the different dataset sizes across models.

Model	Dataset	Validation Accuracy	F1-Score	Test Accuracy	RMSE	Runtime (s)
Logistic Regression (LR)	*df*_25	0.7502	0.64	0.7490	0.50097	10.9
	*df*_50	0.3441	0.33	0.3277	0.8200	24.7
	*df*_75	0.75	0.64	0.7511	0.49889	10.4
LR Hyperparameters	*df*_25	0.7490	0.64	0.8285	0.5010	184.46
	*df*_50	0.3275	0.27	0.3482	0.8201	155.21
	*df*_75	0.7511	0.64	0.7507	0.4989	215.34
Random Forest (RF)	*df*_25	0.9373	0.95	0.9452	0.23412	210.75
	*df*_50	0.9472	0.95	0.9552	0.21154	278.71
	*df*_75	0.9643	0.97	0.9698	0.17376	388.92
Deep Neural Network (DNN)	*df*_25	0.9266	0.93	0.9269	0.27097	95.31
	*df*_50	0.9120	0.91	0.9124	0.29663	142.96
	*df*_75	0.9292	0.93	0.9289	0.26600	134.62
Hybrid RF-DNN	*df*_25	0.9451	0.95	0.9451	0.23428	185.86
	*df*_50	0.9600	0.95	0.9550	0.21224	194.3
	*df*_75	0.9697	0.97	0.9697	0.17399	164.55

Table 3.4: Performance metrics for machine learning models.

Logistic Regression (LR) is a simple and interpretable model, making it easy to understand the relationship between features and outcomes [24]. It also boasts fast training and prediction times, as evidenced by its low runtime of 10.9 seconds for the *df*_25 dataset (see Figure 3.10). However, LR struggles with imbalanced datasets, as seen in its poor performance on *df*_50, where accuracy dropped to 34.41% (see Table 3.4). Additionally, its linear nature limits its ability to capture complex, non-linear relationships in the data, which is reflected in its lower AUC-ROC score compared to other models (see Figure 3.9). Random Forest (RF), on the other hand, demonstrates high accuracy and robustness across all datasets, achieving 96.43% accuracy on *df*_75. Its ability to handle imbalanced data and provide feature importance analysis makes it highly interpretable [33]. However, RF suffers from longer training times, such as the 388.92 seconds recorded for *df*_75 (see Figure 3.10). Deep Neural Networks (DNN) excel at capturing complex, non-linear patterns, achieving 92.92% accuracy on *df*_75. Their flexible architecture allows for customisation with dropout layers and activation functions, enhancing their predictive power [19]. Nevertheless, DNNs require significant computational resources and longer training times, as seen with the 142.96 seconds for *df*_50 (see Figure 3.10), and lack the interpretability of tree-based models. The hybrid RF-DNN model combines the strengths of both Random Forest and Deep Neural Networks, leveraging RF's feature selection capability and DNN's predictive power to achieve the highest accuracy of 96.97% on *df*_75. This approach also reduces computational overhead by focusing on the most important features. However, the hybrid model introduces increased complexity in implementation and tuning compared to standalone models, and its runtime, while efficient, is still longer than simpler models like LR (see Figure 3.10).

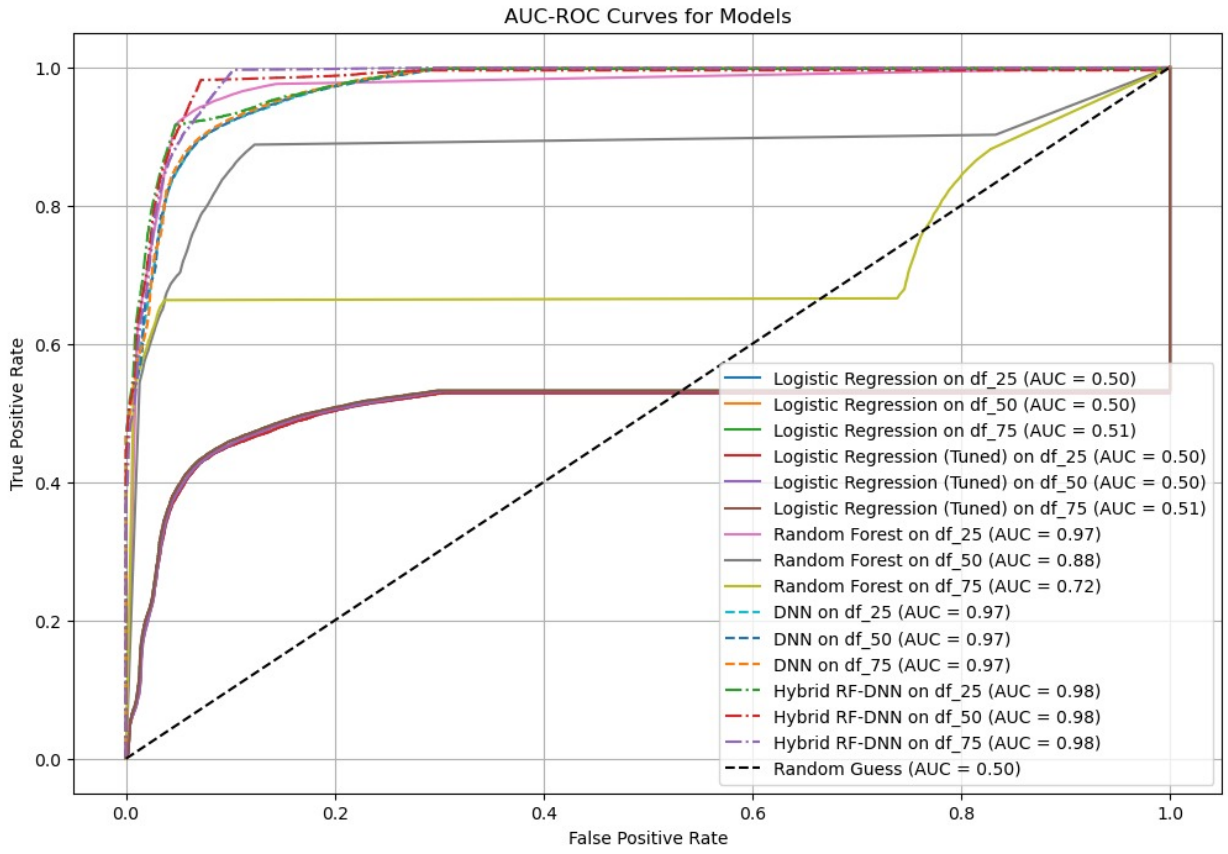


Figure 3.9: AUC-ROC curves for all models across *df*_25, *df*_50, and *df*_75 datasets. .

The hybrid RF-DNN model achieves the highest AUC, outperforming others in distinguishing fraudulent from non-fraudulent users

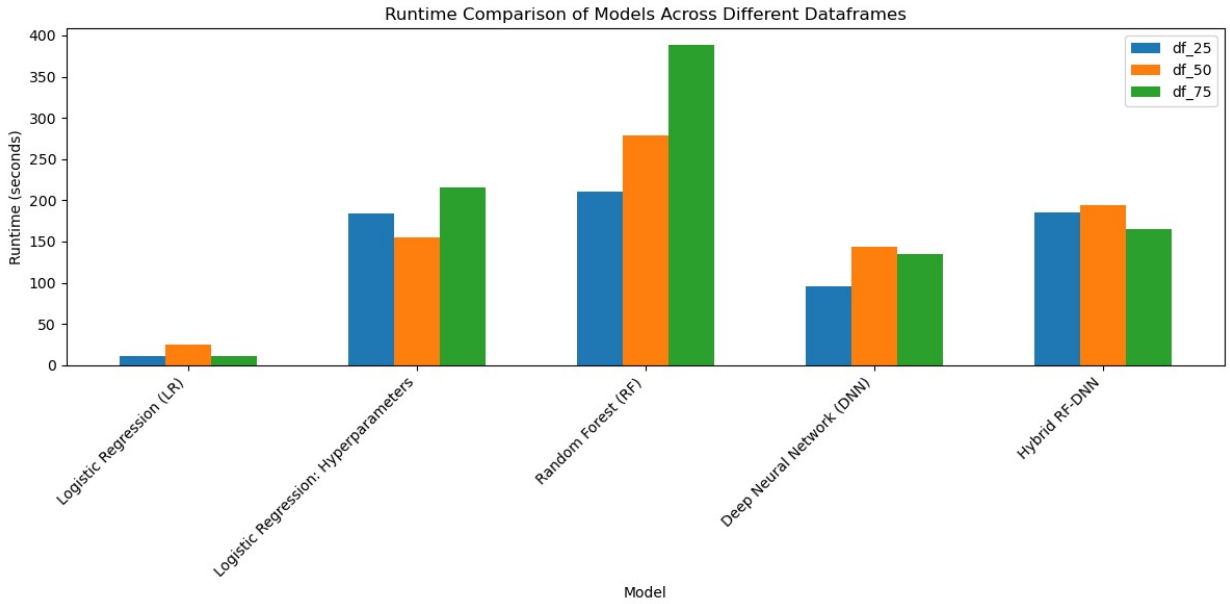


Figure 3.10: Runtime comparisons for all models across *df*_25, *df*_50, and *df*_75 datasets.

Logistic Regression has the lowest runtime, while Random Forest and the hybrid RF-DNN model require longer training times due to their complexity.

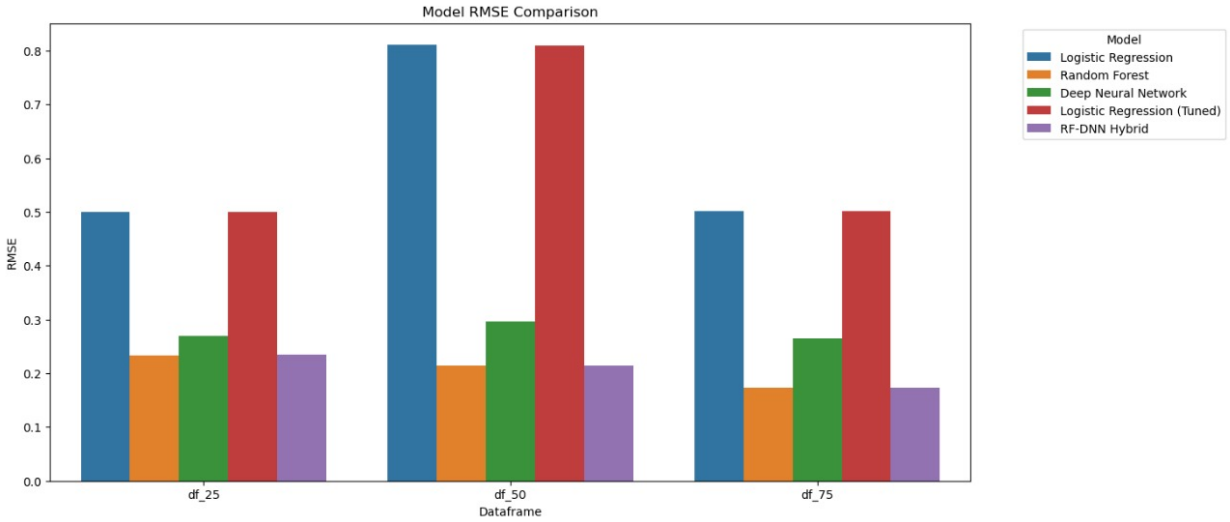


Figure 3.11: RMSE values for all models across *df*_25, *df*_50, and *df*_75 datasets.

The hybrid RF-DNN model achieves the lowest RMSE, indicating the highest predictive accuracy.

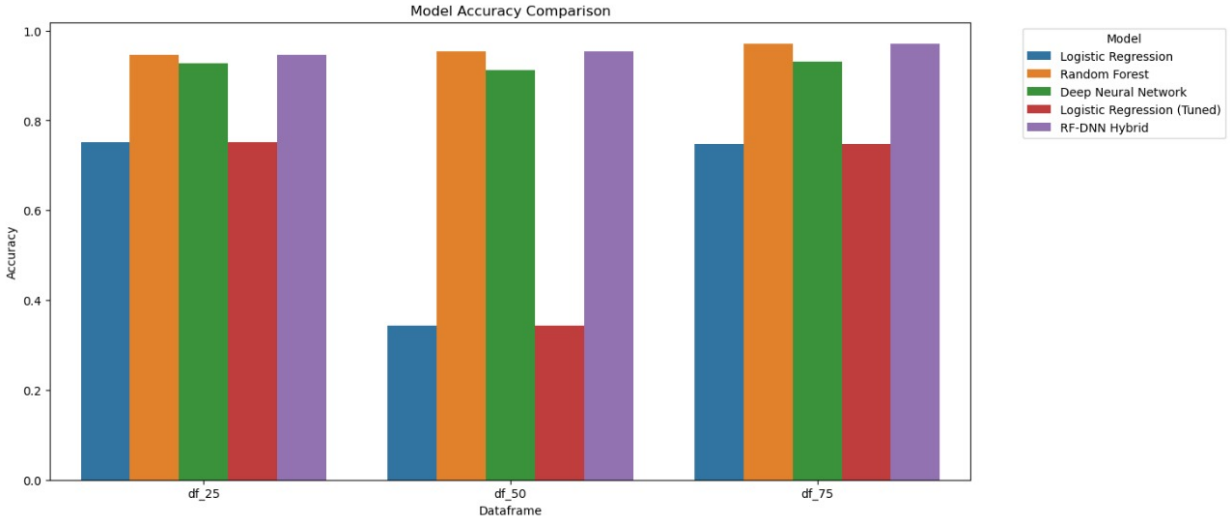


Figure 3.12: Model accuracy for all models across *df*_25, *df*_50, and *df*_75 datasets.

The hybrid RF-DNN model consistently achieves the highest accuracy, followed by Random Forest and Deep Neural Networks.

3.5.2 Discussion

The Receiver Operating Characteristic (ROC) curve analysis provides valuable insights into the performance of the machine learning models across the three datasets (*df*_25, *df*_50, and *df*_75). The ROC curve plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity), and the Area Under the Curve (AUC) summarises the overall performance of a model. An AUC of 1.0 indicates perfect performance, while 0.5 suggests performance no better than random guessing.

Baseline Performance

The dashed black line in Figure 3.9 represents a random classifier (AUC = 0.50), serving as the baseline for comparison. All models are evaluated against this baseline to determine their effectiveness in distinguishing between fraudulent and non-fraudulent users.

Logistic Regression (LR)

The untuned Logistic Regression model shows poor performance, with AUCs around 0.50 for all datasets, indicating it is barely better than random guessing. Even after hyperparameter tuning, the AUC remains close to 0.50, suggesting that logistic regression is unsuitable for this type of data or problem. This is likely due to the non-linear relationships in the data, which LR cannot effectively capture. As shown in Table 3.4, LR achieves an accuracy of 75.02% on *df*_25 but drops significantly to 34.41% on *df*_50, highlighting its limitations with imbalanced datasets.

Random Forest (RF)

The Random Forest model demonstrates varying performance across datasets. On *df*_25, it achieves an excellent AUC of 0.97, but performance decreases to 0.88 on *df*_50 and 0.72 on *df*_75. This decline suggests potential overfitting or that the features in *df*_75 are less predictive. As shown in Table 3.4, RF achieves high accuracy across all datasets (93.73% on *df*_25, 94.72% on *df*_50, and 96.43% on *df*_75), but the decreasing AUC values indicate a need for further investigation into feature engineering and hyperparameter tuning.

Deep Neural Network (DNN)

The DNN model exhibits consistently high performance across all datasets, achieving AUCs of 0.97. This robustness highlights the DNN's ability to capture complex, non-linear patterns in the data. As shown in Table 3.4, DNN achieves accuracies of 92.66% on *df*_25, 91.20% on *df*_50, and 92.92% on *df*_75, with RMSE values of 0.27097, 0.29663, and 0.26600, respectively. However, the model's lack of interpretability and longer training times (142.96 seconds for *df*_50) remain challenges.

Hybrid RF-DNN

The hybrid RF-DNN model combines the strengths of Random Forest and Deep Neural Networks, achieving marginally better performance with AUCs of 0.98 across all datasets. This improvement suggests that leveraging the feature selection capability of RF and the predictive power of DNN can enhance overall performance. As shown in Table 3.4, the hybrid model achieves the highest accuracy (96.97% on *df*_75) and the lowest RMSE (0.17399 on *df*_75). However, the increased complexity and longer runtime (164.55 seconds for *df*_75) must be considered.

Key Observations

- df_25 Performance: All models perform best on *df*_25, suggesting that this dataset contains the most discriminative features or has less noise.
- Logistic Regression's Inadequacy: Logistic regression fails to model the data effectively, indicating a non-linear relationship between features and the target variable.
- Random Forest: The drop in Random Forest performance on *df*_75 necessitates further investigation.
- DNN's Robustness: The DNN model demonstrates consistent performance across all datasets, showcasing its ability to learn complex patterns.
- Hybrid Model's Incremental Improvement: The hybrid model offers a marginal improvement, suggesting potential benefits in combining different model architectures.

3.6 Chapter Summary

This chapter presented a comprehensive approach to detecting electricity theft using machine learning techniques. It detailed the process of data collection and preprocessing, followed by feature selection through Principal Component Analysis (PCA) to identify significant factors influencing non-technical losses (NTLs). Various machine learning models were developed and evaluated to detect electricity theft, with strategies to address class imbalance in the dataset. The chapter also discussed the deployment of the model, leveraging Flask for the backend and a web application for real-time monitoring. Results demonstrate the effectiveness of the proposed system, with model performance evaluated through key metrics, and the chapter concluded with a discussion on the practical implications and potential for further improvements.

Chapter 4

Smart Transducer-based Electricity Theft Detection Scheme

4.1 Smart Transducer-based Electricity Theft Detection Methodology

This chapter presents a smart transducer-based strategy for detecting electricity equipment theft using a combination of hardware, networking, and software techniques. The system integrates a sound sensor module, an electronic relay, an ESP32 microcontroller with a SIM900L module, and an ultrasonic proximity sensor to detect intrusions into electrical cabinets. Designed as a robust IoT solution, it automates theft detection by sending SMS alerts to a specified cellphone number upon unauthorised access. The chapter details the methodology, covering data collection, pre-processing, and system implementation, followed by the mathematical modelling of the detection system, including an approximate second-order model, frequency analysis, and stability assessment. Finally, the results and discussion section evaluates the system's effectiveness, demonstrating its reliability in identifying unauthorised access. This work represents an advancement over previous studies [90], by introducing a real-time, advanced automated theft detection system.

4.1.1 Data Collection and Pre-processing

In this study, all noise data were meticulously generated through controlled physical impacts on the cabinet, simulated by the precise application of a hammer. Various impact scenarios were meticulously crafted, encompassing both single and multiple impacts to emulate potential intrusion events. Additionally, continuous noise data akin to that generated by a metal grinder during cutting operations was meticulously recorded. It is imperative to note that all data collection experimental trials were conducted under real-world conditions, specifically to function on an intrinsically safe cabinet such as the HUAWEI 5G telecommunications outdoor cabinet, distinguished by its IP55 protection ratings, ensuring robustness against environmental factors.

The raw signal detected by the sound sensor module necessitated preprocessing due to its inherent instability characterised by fluctuating amplitudes. To mitigate this instability and enhance signal integrity, appropriate logarithmic transformations were meticulously applied, as detailed in Equation 4.1. Furthermore, an iterative amplitude correction method was systematically employed to ensure the fidelity of the signal. Notably, the sound sensor module was equipped with a variable resistor, meticulously optimised to minimise sensitivity and mitigate false positives. Subsequently, the acquired dBA values from the sound sensor module were meticulously benchmarked against those obtained using the DecibelX smartphone application, meticulously running on iOS app version 17 on an iPhone 14 Pro Max, thus ensuring a meticulous validation process and yielding more precise and reliable results. The sound sensor was calibrated to have a lower dBA range of 64 dBA which is the maximum threshold

noise level of an operating cabinet. In contrast, the ultrasonic sensor yielded raw data readings of impeccable accuracy, obviating the need for preprocessing.

$$\text{OutputSoundSignal} = A \times \log(\text{raw_soundsignal}) \tag{4.1}$$

Here, A represents the desired amplitude, `raw_soundsignal` denotes the unprocessed input signal, and `OutputSoundSignal` signifies the meticulously processed sound signal converted to dBA for subsequent analysis citemabokodesign.

Figure 4.1 depicts the raw output signal before undergoing any form of data processing, while Figure 4.2 illustrates the system's response during the recording of cabinet sound after data processing. Notably, the processed signal exhibits a commendable level of stability. It is worth highlighting that all graphical representations were meticulously generated utilising the Arduino's serial plotter monitor.

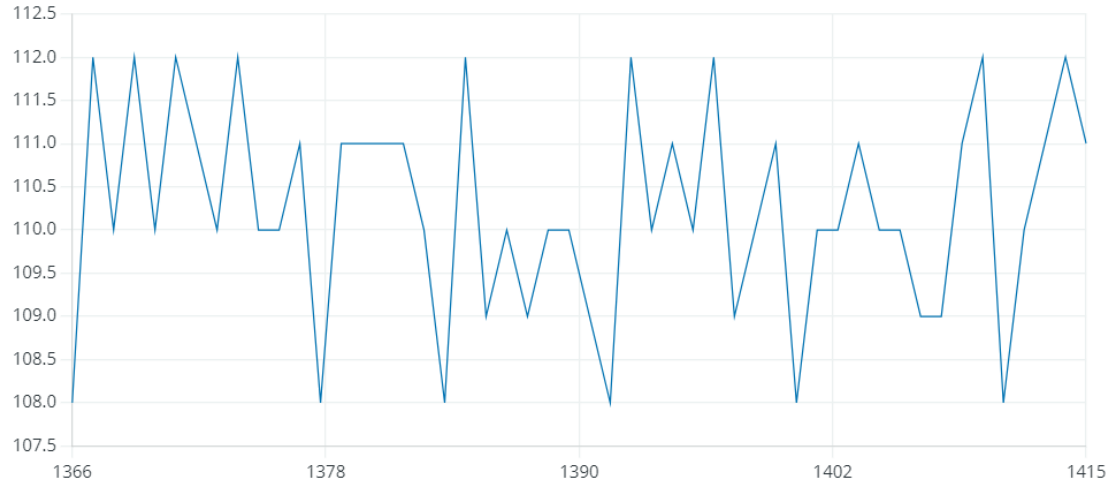


Figure 4.1: Signal output before data processing.

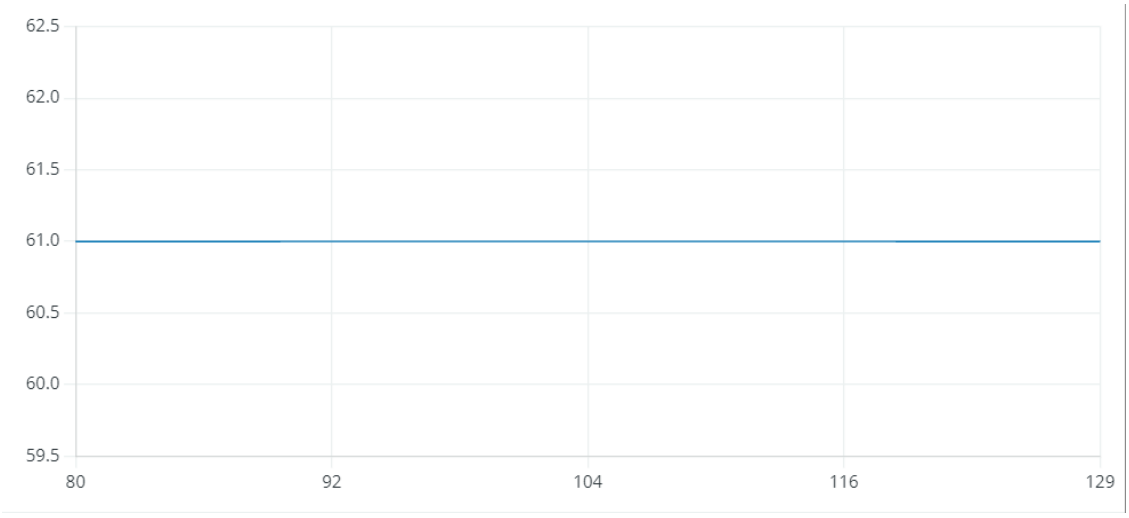


Figure 4.2: Signal output after data processing.

4.1.2 System Design and Implementation

All source code sketches used for this project can be found on this platform: `https://drive.google.com/drive/folders/1UshAEfDYN1-sb8CboAzXM4-s1hHEc_Ne?usp=sharing`

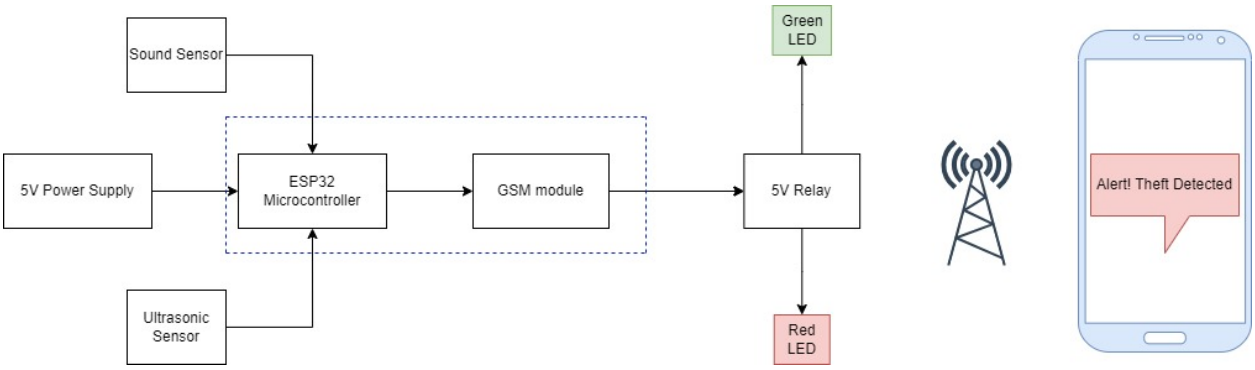


Figure 4.3: End to end block diagram overview of the system.

Figure 4.3 illustrates the comprehensive block diagram overview of the system, wherein data acquisition is accomplished through the utilisation of both the KY-037 microphone sound sensor and the HC-SR04 ultrasonic distance sensor. The process of data processing, control, and automation is exemplified in Figure 4.4 which represents the system's experimental setup, employing the Arduino IDE platform for the software program. To enhance portability, reduce the system's dimensions, and reduce the system's complexity, an ESP32 with integrated sim900L module is employed to avoid the manual integration of components. Furthermore, this advancement renders the system notably sophisticated compared to the design delineated in the study by M. Maboko. [90], as it incorporates the capability to transmit SMS alerts to a designated cellphone. This feature enables timely notification of personnel, whether within or outside the office premises, regarding potential incidents of theft or security breaches. Such enhancements underscore the system's heightened efficacy in bolstering security measures and facilitating prompt response protocols.

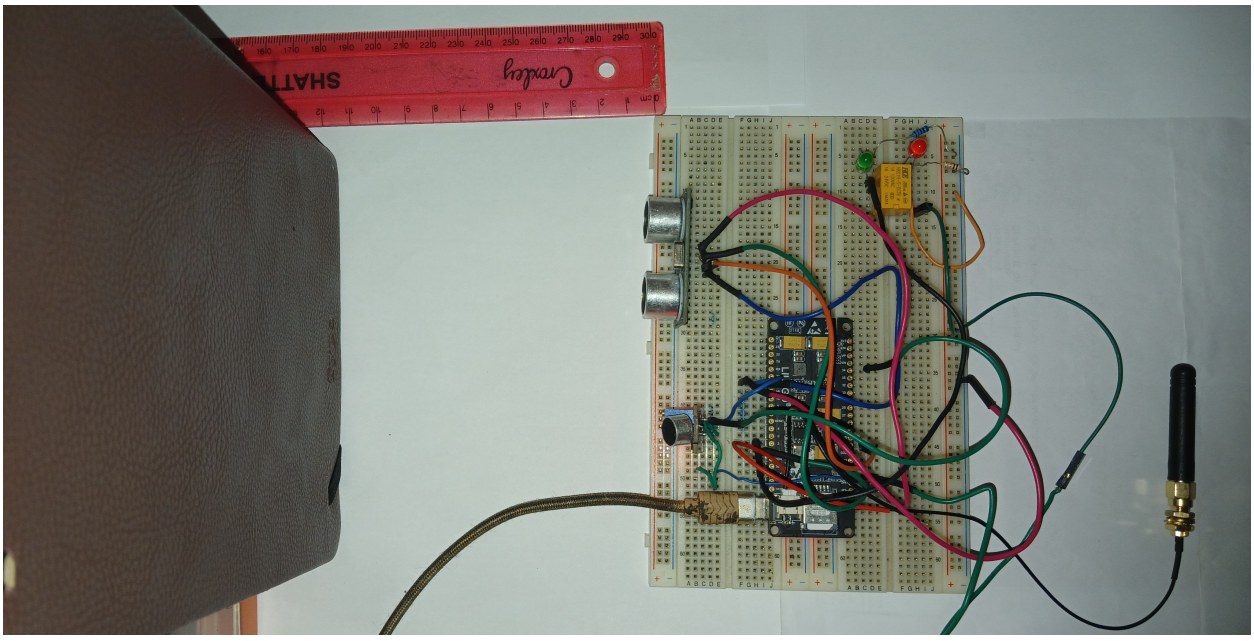


Figure 4.4: Representation of the system's experimental setup

Power provisioning for the system is facilitated via a 5V USB connection originating from the System Management Unit (SMU) when the HUAWEI infrastructure or similar system is used, which is directed towards the VCC and GND pins of the ESP32sim900L module. Similarly, a battery can be used for stand-alone applications or with other IoT systems. Notably, the digital information pins 2 of the ESP32sim900L module serve as the system's output, thereby activating the digital input of the rectifier when prompted upon coil energisation or de-energisation of the relay. Additionally, pin 34 designates an analog input pin associated with the sound detector module, while 13 denotes a digital input pin connected to the ultrasonic sensor module. The transition from the Arduino Uno to be used in [90] to the ESP32sim900L module represents a strategic shift aimed at enhancing system efficiency and adaptability. Figure 4.5 shows the comprehensive system schematic diagram.

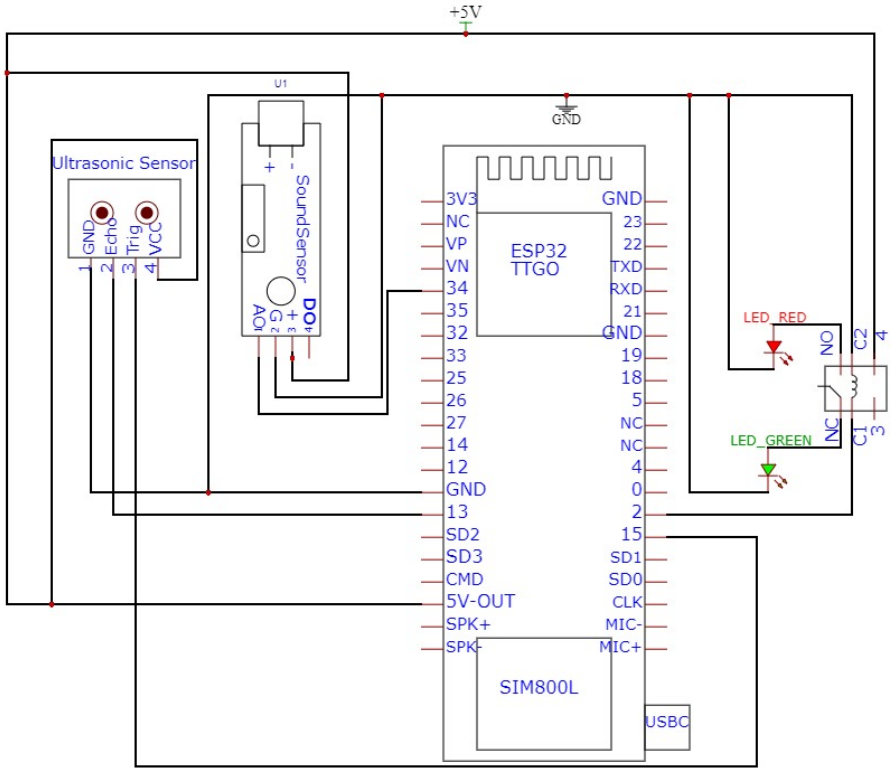


Figure 4.5: Electricity theft detection system schematic diagram.

An electronic relay is an electromechanical device that is used as a switch. This device consists of multiple contact input terminals and multiple contact output terminals. Configured as Normally Closed (NC) or Normally Open (NO) upon coil energisation. Multiple input-output contacts facilitate the solution in terms of scalability and efficient logical programming. A 5V relay was added to this solution, directly connected to the output LEDs of the system.

4.2 Smart Transducer System Mathematical Design

The smart transducer system design involves analysing a 3rd-order system and approximating it with a 2nd-order system. The transfer functions are derived based on circuit parameters, and frequency analysis is conducted to evaluate system performance [113].

4.2.1 Mathematical Modelling

To derive the system transfer function, each component was analysed:

– Microphone: Modelled as a first-order system with gain K_{mic} and time constant τ_m [114].

$$H_{mic}(s) = \frac{K_{mic}}{\tau_m s + 1} \tag{4.2}$$

– Control System: The ESP32 processing delay is modeled as a first-order system with gain K_c and time constant T_c.

$$H_c(s) = \frac{K_c}{T_c s + 1} \tag{4.3}$$

– Relay: Introduces an additional delay modelled with a time constant τ_r.

$$H_r(s) = \frac{1}{\tau_r s + 1} \tag{4.4}$$

– Acoustic Path: The speed of sound c contributes to the system dynamics.

$$H_{acoustic}(s) = c \tag{4.5}$$

The overall system transfer function is obtained by cascading these subsystems:

$$H(s) = H_{mic}(s)H_c(s)H_r(s)H_{acoustic}(s) \tag{4.6}$$

The original system parameters are as follows:
– $K_{mic} = 1.5$ (Mic Gain)
– $K_c = 2.0$ (Control Gain)
– $c = 343$ (Speed of sound in m/s)
– $\tau_m = 0.01$ (Time constant - Microphone)
– $T_c = 0.02$ (Time constant - ESP32 Processing)
– $\tau_r = 0.05$ (Time constant - Relay)
The resulting 3rd-order transfer function is given by:

$$H(s) = \frac{1029}{0.00001s^3 + 0.0035s^2 + 0.08s + 1} \tag{4.7}$$

4.2.2 Approximate 2nd-Order System

To simplify the system, an approximate 2nd-order model is used with parameters:
– $K = 120$ (System gain)
– $w_1 = 8$ (First pole)
– $w_2 = 50$ (Second pole)
The transfer function for the approximate system is:

$$H_{approx}(s) = \frac{120}{s^2 + 58s + 400} \tag{4.8}$$

4.2.3 Frequency Analysis and Stability

The Bode plots in Figure 4.6 illustrate the system characteristics [115]:
– Bode Plot - Magnitude Response: This plot illustrates how the magnitude (in decibels) of the system's transfer function varies with frequency (on a logarithmic scale). The plot shows a decreasing trend, suggesting that the system acts as a low-pass filter, attenuating higher frequencies.
– Bode Plot - Phase Response: This plot shows how the phase shift of the output signal changes with frequency. The phase response starts at a certain point and becomes more negative as the frequency increases, which is typical for systems with poles and zeros that introduce phase shifts.

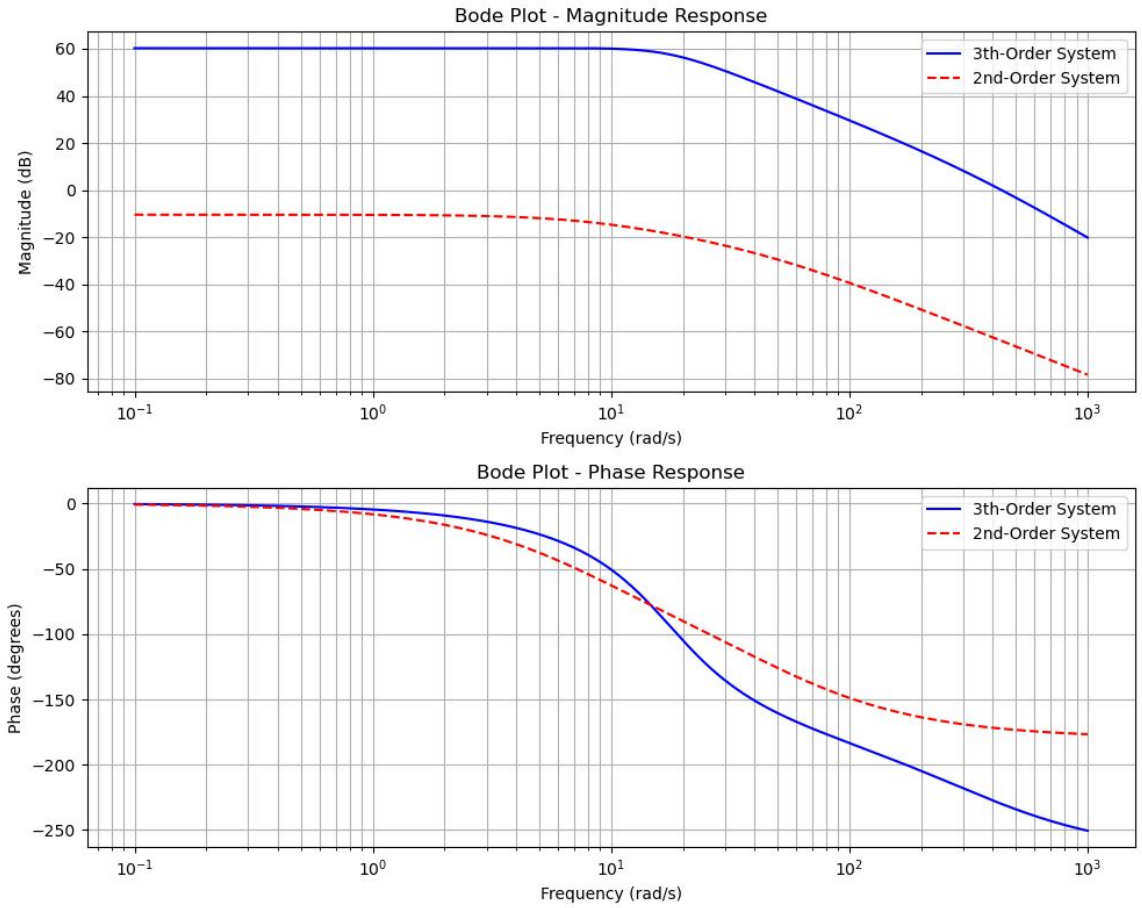


Figure 4.6: System design schematic diagram

The key system parameters are summarised in the following table:

System	Transfer Function	Poles	Bandwidth	Stability
Original 3rd-order	$\frac{1029}{0.00001s^3+0.0035s^2+0.08s+1}$	$-100, -200, -500$	10 rad/s	Stable
Approximate 2nd-Order	$\frac{120}{s^2+58s+400}$	$-8, -50$	20 rad/s	Stable

Table 4.1: System Transfer Functions, Poles, Bandwidth, and Stability

4.2.4 Trade-offs in System Approximation

Approximating a higher-order system with a lower-order model introduces inherent trade-offs that influence system behaviour, particularly in precision, transient response, and frequency-domain characteristics. This simplification reduces complexity to facilitate analysis and controller design but entails compromises that warrant careful evaluation.

4.2.5 Loss of Precision in Dynamic Representation

The third-order system, with three poles (-100,-200,-500), captures a richer set of dynamic states, reflecting intricate transient behaviours and higher-frequency responses. Reducing it to a second-order model eliminates the least dominant pole 500, sacrificing detail in the system's dynamic representation.

This loss affects the fidelity of transient characteristics, such as overshoot, settling time, and damping, which are critical for accurate system modelling [116].

4.2.6 Frequency Domain Considerations

Order reduction alters the frequency response, notably bandwidth and phase shift. The third-order system's bandwidth is approximately 10 rad/s, while the second-order approximation extends to 20 rad/s (see Table 4.1). This increase suggests that the approximation preserves low-frequency behaviour but modifies high-frequency attenuation, as illustrated in the Bode plots (Figure 4.6). While suitable for applications dominated by lower frequencies, the second-order model may fail to capture higher-order dynamics essential for precise control at elevated frequencies [117].

4.2.7 Impact on Transient Response

For systems that are critically damped or overdamped, a second-order approximation may suffice, aligning closely with dominant dynamics. However, if the neglected pole significantly shapes the transient response as the pole at 500 might with its faster dynamics the approximation can misrepresent key metrics like rise time, peak amplitude, and settling behaviour. This discrepancy is evident when comparing step responses: the third-order system exhibits a more nuanced evolution, while the second-order model oversimplifies rapid transients, potentially underestimating response speed [118].

4.2.8 Control Implications

From a control perspective, second-order systems are advantageous due to their well-established analytical frameworks, simplifying controller synthesis and real-time implementation [119]. However, neglecting the pole at -500 may compromise high-fidelity tracking or disturbance rejection in demanding scenarios. For instance, unmodeled fast dynamics could necessitate additional compensation in control gains, increasing design complexity if robust performance is required.

4.2.9 Functionality

Upon detection of a sound level surpassing 80 dBA and, observing a distance exceeding 15 cm between the sensor system and the cabinet door, the system classifies the event as indicative of theft. In response, activation of the red LED indicator ensues, accompanied by the transmission of a high signal to the digital input dry contact of the rectifier. Moreover, immediate dissemination of alarm alerts via SMS to the network monitoring personnel ensues.

In instances where the sound level falls below 80 dBA, yet the distance between the sensor system and the cabinet door exceeds 15 cm, the system interprets such occurrences as suggestive of potential theft or a routine site visit. In this context, illumination of the red LED indicator occurs, alongside the relay of a high signal to the digital input dry contact of the rectifier. Consequently, expeditious dispatch of alarm alerts via SMS to the network monitoring personnel is initiated.

Additionally, if the sound level surpasses 85 dBA, indicative of an increased likelihood of theft, the system proceeds to activate the red LED indicator and transmit a high signal to the digital input dry contact of the rectifier. Concurrently, prompt dissemination of alarm alerts via SMS to the network monitoring personnel is facilitated, thereby ensuring timely awareness and response to potential security breaches. The electricity theft detection flow functionality diagram is depicted below in Figure 4.7.

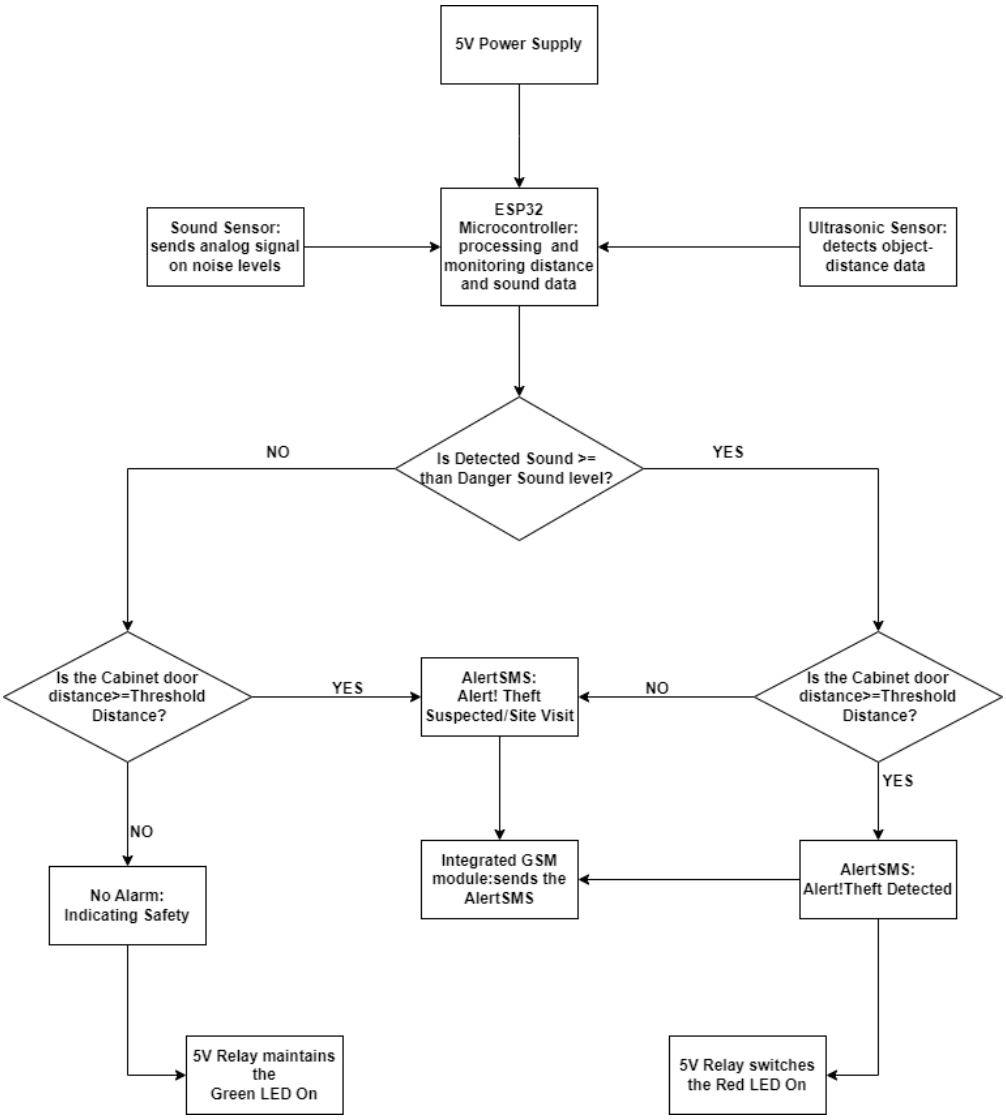


Figure 4.7: Electricity equipment theft detection flow diagram.

4.3 Results and Discussion

Mathematically second-order approximation balances analytical simplicity and computational efficiency against a loss of precision in fast transients and high-frequency behavior. Its suitability hinges on application needs for real-time control in resource-constrained environments. The trade-off is justified for applications demanding accurate high-frequency response, retaining the third-order model is preferable. This decision underscores the importance of aligning model complexity with operational requirements [118]

The implemented prototype attains an average response time of 3.9 seconds across six samples, as depicted in the figure below illustrating the alarm alerts displayed on a cellular device. Notably, each site is designated with a distinct cellphone number for effective communication. Moreover, the tabulated results during testing, along with their corresponding response times, are presented in Table 1. These findings underscore the efficacy of the prototype in promptly detecting and addressing security concerns across various sites.

Figure 4.8 depicts alarm alerts sent to a mobile cellphone that supports SMS messaging or (General Packet Radio Service) GPRS technology. GPRS is mobile data service that enables data transmission using the GSM (Global System for Mobile Communications) network.

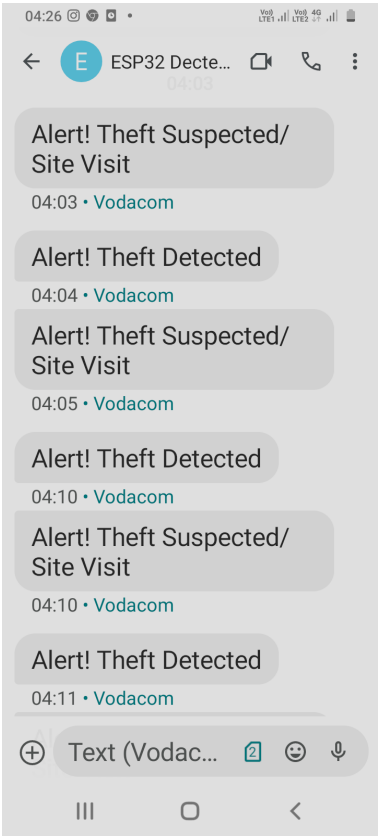


Figure 4.8: shows the alarm alerts sent to a mobile cellphone

Table 4.2: Response Time for Test Samples

Test Sample	**Response Time (s)**
Test sample 1	3.3
Test sample 2	3.8
Test sample 3	4.1
Test sample 4	3.9
Test sample 5	4.2
Test sample 6	3.7
Average Response	**3.9**

Figure 4.9, 4.10, 4.11, and 4.12 illustrate the graphical depiction of the system's response when noise is induced by striking the cabinet, simulating intrusion scenarios. Arduino's IDE's serial plotter monitor was used for the graphical representations of the conducted experiments. Additionally, Figure 4.13 presents a visual representation of Arduino's object distance detection in centimeters and sound intensity in decibels (dBA) during intrusion events, while 4.14 provides a snapshot of the same parameters when no intrusion occurs.

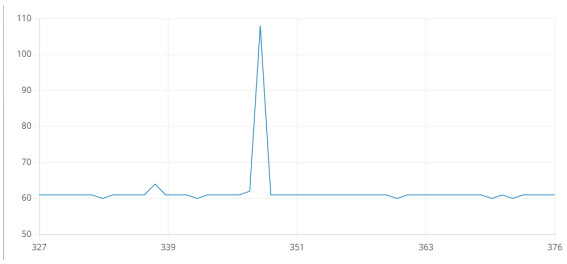


Figure 4.9: Single loud noise generated.

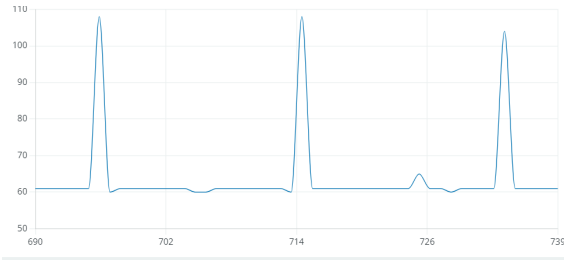


Figure 4.10: Multiple loud noises generated.

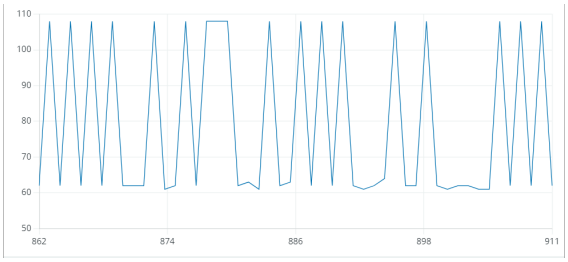


Figure 4.11: Continuous loud noise generated (grinder).

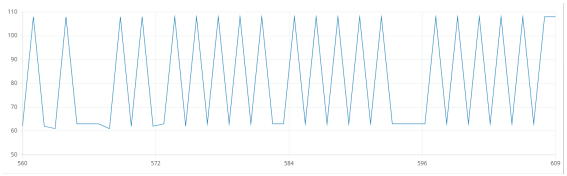


Figure 4.12: Continuous loud noise generated (masonry drill bit).

```
04:09:54.922 ->
04:09:54.922 -> Alert! Theft Suspected/Site Visit
04:09:56.859 -> SOUND DETECTED: 61
04:09:57.390 -> OBJECT DISTANCE: 27
04:09:57.390 ->
04:09:57.390 -> Alert! Theft Suspected/Site Visit
04:09:59.350 -> SOUND DETECTED: 108
04:10:04.903 -> OBJECT DISTANCE: 28
04:10:04.903 ->
04:10:04.903 ->                 Alert! Theft Detected
04:10:10.924 -> SOUND DETECTED: 61
04:10:11.492 -> OBJECT DISTANCE: 26
04:10:11.492 ->
04:10:11.492 -> Alert! Theft Suspected/Site Visit
```

Figure 4.13: Object distance detection in cm and sound in dBA on the serial monitor for intrusion scenarios.

```
04:23:48.276 ->
04:23:48.276 -> SOUND DETECTED: 61
04:23:48.764 -> OBJECT DISTANCE: 10
04:23:48.764 ->
04:23:48.764 -> SOUND DETECTED: 61
04:23:49.282 -> OBJECT DISTANCE: 10
04:23:49.282 ->
04:23:49.282 -> SOUND DETECTED: 61
04:23:49.782 -> OBJECT DISTANCE: 10
04:23:49.782 ->
04:23:49.782 -> SOUND DETECTED: 61
04:23:50.283 -> OBJECT DISTANCE: 10
04:23:50.283 ->
04:23:50.283 -> SOUND DETECTED: 61
04:23:50.783 -> OBJECT DISTANCE: 10
```

Figure 4.14: Image 2 of object distance detection in cm and sound in dBA on the serial monitor for no intrusion scenario.

4.4 Cost Analysis of the Smart Transducer System

To assess the practical applicability of the proposed smart transducer system, particularly in resource-constrained environments such as developing regions, a detailed cost analysis is essential. This section evaluates the economic feasibility of the system by breaking down the costs of its components, analysing cost-effectiveness relative to electricity theft losses, and discussing scalability implications. The analysis aligns with the research objective of developing a cost-effective solution for detecting electricity theft in smart grids. Table 4.3 shows the breakdown of the component's costs.

Component	Quantity	Unit Cost (ZAR)	Total Cost (ZAR)
KY-037 Microphone Sensor	1	R 20.00	R 20.00
HC-SR04 Ultrasonic Sensor	1	R 28.00	R 28.00
ESP32 + SIM800 Module	1	R 890.00	R 890.00
SIM Card	1	R 5.00	R 5.00
5V Relay Module	1	R 30.50	R 30.50
LED Indicators	2	R 2.96	R 5.92
Power Supply (5V)	1	-	-
Battery (9V)	1	R 40.25	R 40.25
PCB or Breadboard (8.3x5.5cm)	1	R 23.00	R 23.00
Total	-	-	**R 1042.67**

Table 4.3: Cost breakdown of smart transducer components

4.4.1 Cost-Effectiveness Evaluation

In South Africa, municipalities like Ekurhuleni, Tshwane, and Johannesburg reported losses exceeding R 3 billion in 2018 due to non-technical losses (NTLs), with a significant portion attributed to theft [7]. Assuming a conservative estimate of 1000 theft incidents annually across these regions, the average loss per incident is approximately R 3000. Deploying the proposed system at a cost of R 1042.67 per unit could prevent a single theft incident, yielding a potential return on investment (ROI) if the prevented loss exceeds the deployment cost.

For a single cabinet, the cost-benefit ratio can be expressed as:

$$\text{ROI} = \frac{\text{Value of Prevented Loss}}{\text{System Cost}} = \frac{\text{R } 3000}{\text{R } 1042.67} \approx 2.88 \tag{4.9}$$

An ROI of 2.88 indicates that the system could recover its cost nearly threefold by preventing just one theft event, suggesting high cost-effectiveness for high-risk areas. However, this estimate assumes successful detection and intervention, which depends on factors such as response time.

4.4.2 Scalability and Deployment Considerations

Scaling the system across multiple electrical cabinets introduces additional cost considerations. For a network of 100 cabinets, the total hardware cost would be:

$$\text{Total Cost} = 100 \times \text{R } 1042.67 = \text{R } 104,267 \tag{4.10}$$

Additional expenses, such as installation (estimated at R 200 per unit) and maintenance (e.g., battery replacement every 2 years at R 40.25), could increase the initial investment to approximately R 125,000 for 100 units. In comparison, annual NTL losses in South Africa often exceed billions of Rands [5, 6], suggesting that even a modest reduction in theft (e.g., 5% of R 1 billion = R 50 million) would dwarf deployment costs.
To enhance scalability, bulk procurement could reduce unit costs. For instance, negotiating a 20% discount on the ESP32 + SIM800 module (lowering it from R 890.00 to R 712.00) would decrease the per-unit cost to R 864.67, reducing the 100-unit total to R 86,467. Furthermore, integrating the system with existing IoT platforms minimises additional infrastructure costs, leveraging pre-existing smart grid investments [8].

4.4.3 Implications for Developing Regions

In developing economies like South Africa, where electricity theft contributes to economic instability [13], the proposed system's affordability is a critical advantage. At under R 1050 per unit, it is

significantly cheaper than commercial anti-theft solutions, such as advanced metering infrastructure upgrades (often exceeding R 10,000 per installation) or continuous monitoring systems with high operational costs [14]. The use of off-the-shelf components and minimal reliance on external power further reduces deployment barriers in rural or underfunded areas.
However, challenges remain. The system's reliance on GSM communication incurs ongoing SIM card and data costs (e.g., R 10 to R 20 monthly per unit), which could accumulate over time. Exploring alternatives like Long Range Wide Area Network (LoRaWAN) for low-cost, low-power communication could further optimise expenses [120]. Additionally, the system's temperature limitation (40°C maximum, Section 5) may require ruggedised components for hotter climates, potentially increasing costs.

4.5 Chapter Summary

This chapter implemented a smart transducer-based strategy for detecting electricity equipment theft. The approach involves the utilisation of a sound sensor module, an electronic relay, ESP32 with a SIM900L module, and an ultrasonic proximity sensor to identify intrusions into electrical cabinets. In this work, the system was designed as a robust IoT solution, automating the process by sending SMS alerts to a specified cellphone number. This advancement is not in [90]. Deployment as well as ongoing probable cost were also detailed. In this chapter, methods that combine hardware, networking, and software techniques are focused on.

Chapter 5

Conclusion

5.1 Research Summary

This study addresses the following research question:

How best can an efficient, cost-effective intelligent predictive classification algorithm for detecting electricity theft be designed and implemented, while leveraging microcontroller techniques to enhance accuracy and effectiveness?

5.2 Future Work Recommendations

5.2.1 Machine Learning Solution

To further enhance model performance and robustness, several strategies are recommended. Advanced feature engineering should be explored to improve predictive power, particularly for Random Forest on df_75, by leveraging domain-specific transformations and feature selection techniques such as mutual information and recursive feature elimination. Comprehensive hyperparameter optimisation, using methods like Bayesian optimisation and grid search, can further refine model performance, especially for Random Forest and DNN architectures [59]. Robust cross-validation techniques, including stratified k-fold and nested cross-validation, should be employed to enhance model generalisability and mitigate overfitting risks [105]. Additionally, model explainability and transparency can be improved through interpretability techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), providing insights into the decision-making processes of complex models such as DNN and the hybrid RF-DNN [121]. Unsupervised learning methods, including clustering algorithms like k-means and DBSCAN, should also be investigated to identify hidden patterns in unlabeled data, improving fraud detection capabilities [122]. Furthermore, ensemble and hybrid modelling approaches, such as stacking and boosting, could be explored to combine the strengths of different models for enhanced classification performance. By integrating these techniques, the detection framework can achieve higher accuracy, improved interpretability, and better adaptability to evolving electricity theft patterns.

5.2.2 Smart Transducer Solution

To enhance the smart transducer system, several improvements can be considered. Hardware optimisation can be explored by investigating alternative transducer components or digital signal processing techniques to enhance response time and reduce system lag [123]. Implementing adaptive filtering techniques can improve signal accuracy, noise suppression, and robustness under varying conditions. Higher-order approximations such as balanced truncation or singular perturbation methods should be explored to achieve better approximations while preserving essential dynamics [124]. Real-time test-

ing on the ESP32 microcontroller can be conducted to verify performance under actual conditions and fine-tune parameters accordingly. Machine learning-based models can be integrated for predictive system control, enhancing responsiveness and adaptability to environmental changes. Robust control techniques such as H-infinity control or sliding mode control can be applied to ensure stability under uncertain operating conditions [125]. Additionally, optimising the system to achieve improved frequency response by tuning the gain and compensating for phase lags is recommended. Validating theoretical models against real-world experimental results will refine the system and improve accuracy. Multi-sensor fusion can be implemented to integrate additional sensors, improving system robustness and providing better environmental awareness for enhanced decision-making [126]. Lastly, exploring low-power optimisations for the ESP32 can improve energy efficiency, by employing components such as LM805 voltage regulator and a fuse can serve to safeguard the circuit against potential voltage fluctuations exceeding 5V.

The system's static characteristic temperature presents a critical constraint on its viability. Currently, the ESP32 microchip operates within a temperature range of up to 85°C. Conversely, the microphone and ultrasonic sensor detector have a substantially lower maximum operating temperature of 40°C. Consequently, the system's functionality is restricted to environments where temperatures remain below 40°C. It is imperative to explore alternative components with greater resilience to elevated temperatures for potential integration in future iterations of the system.

In forthcoming enhancements, it is recommended to incorporate a NEO 6M GPS module into the detection system device. This addition would enable the transmission of geographic coordinates along with the alert SMS, augmenting the system's functionality beyond solely relying on the SIM contact number associated with the respective base station. Such integration would significantly enhance the comprehensiveness and effectiveness of the system.

The prototype does not necessitate a protective enclosure due to its placement within IP55 rated electrical cabinets, ensuring sufficient safety measures. Nonetheless, considering aspects of portability and longevity, the assembly of a protective enclosure could extend the operational lifespan of the product. Consequently, the product will be affixed to the existing safety enclosure in an electrical cabinet for the purposes of this study.

5.3 Conclusion

This study demonstrated the effectiveness of various machine learning models for electricity theft detection, with the custom hybrid RF-DNN model emerging as the top performer due to its high accuracy, low RMSE, and superior AUC-ROC scores across all datasets (see Figures 3.9, 3.11, and 3.12). Logistic Regression, while fast and interpretable, struggled with imbalanced data and non-linear relationships, as evidenced by its lower accuracy and AUC-ROC scores. Random Forest provided robust performance and interpretability but at the cost of longer training times. Deep Neural Networks excelled in capturing complex patterns but required significant computational resources and lacked interpretability. The hybrid RF-DNN model successfully combined the strengths of RF and DNN, though it introduced additional implementation complexity. Future work will focus on fine-tuning hyperparameters, such as tree depth for Random Forest and learning rate for DNN, to further optimise performance.

Subsequently, this section delineates the development of a novel smart transducer system devised to counteract electrical cabinet equipment theft. The system comprises a sound sensor module, an ultrasonic distance sensor element, and an ESP32 microcontroller with an integrated sim900L module to send out SMS alerts to network monitoring personnel. Notably, the solution was meticulously crafted to function within the confines of a zone 2 hazard area. The raw output signal from the sound sensor underwent preprocessing via judicious signal transformations. Subsequently, comprehensive testing results and a discerning critical analysis were meticulously documented. Although the ML and IoT systems were developed as independent components, they form a complementary hybrid framework.

The ML system is designed to detect anomalous consumption from smart meter data. In contrast, the IoT-based transducer system provides physical layer monitoring and tamper detection for the smart meter cabinet. When deployed together, the system offers a dual-layered fraud detection capability. This solution demonstrates versatility by seamlessly integrating into any IoT system with nominal or no modifications. The realised solution embodies attributes of power efficiency, cost-effectiveness, real-time functionality, and high accuracy.The implemented prototype attains an average response time of 3.9 seconds over 6 samples, within an operational range spanning from 64 dBA (tested maximum operating cabinet noise) to 120 dBA.

Appendix A

A.1 Clean Input Data

In this section, the eleven features of the dataset are presented. The data has undergone stages of data pre-processing as indicated in Section 3.3.1. The plots played an important role in the identification of which features contribute the most to the final submeters as well as which can be ignored during the process of feature selection. Below are the plots of features of the data used in kW.
The code below developed by the author details the use of statistical methodology to calculate the Z-score and remove outliers that may affect the model performance [56]. The sudo code snippet is presented below for a dataframe called `df_daily`.

```
import numpy as np
from scipy import stats

# Select numeric columns
numeric_cols = df_daily.select_dtypes(include=np.number).columns

# Calculate Z-scores
z_scores = stats.zscore(df_daily[numeric_cols])

# Define a threshold (3)
threshold = 3

# Identify outliers for each column
outliers = (np.abs(z_scores) > threshold).any(axis=1)

# Remove outliers from the dataframe
df_no_outliers = df_daily[~outliers]
```

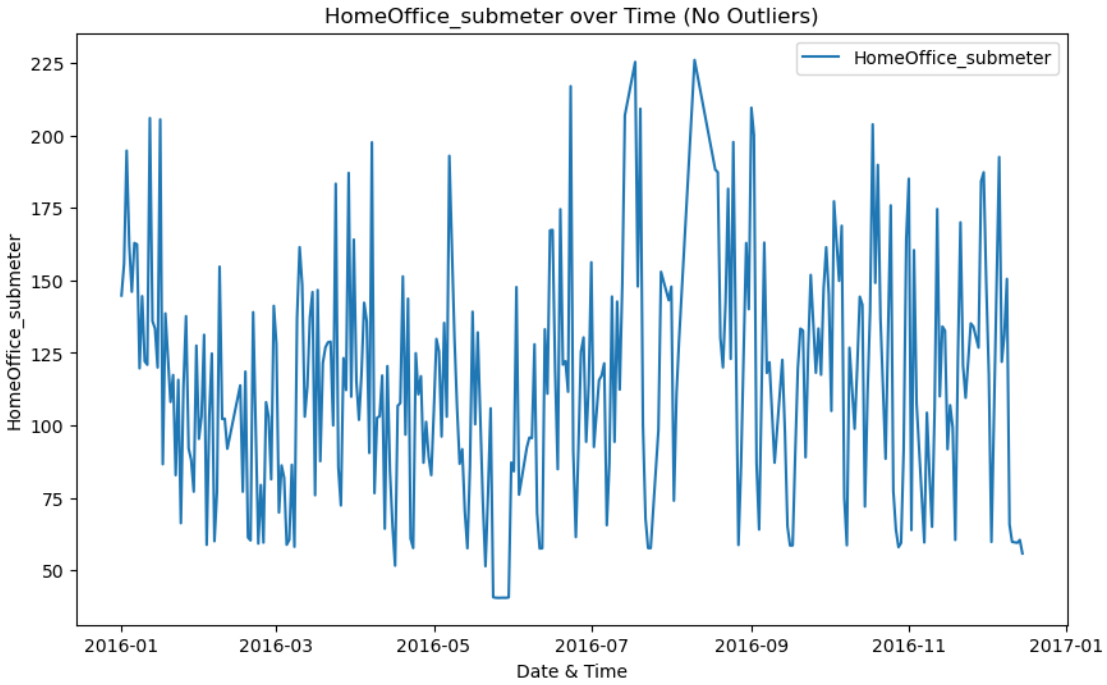


Figure A.1: Home office power consumption

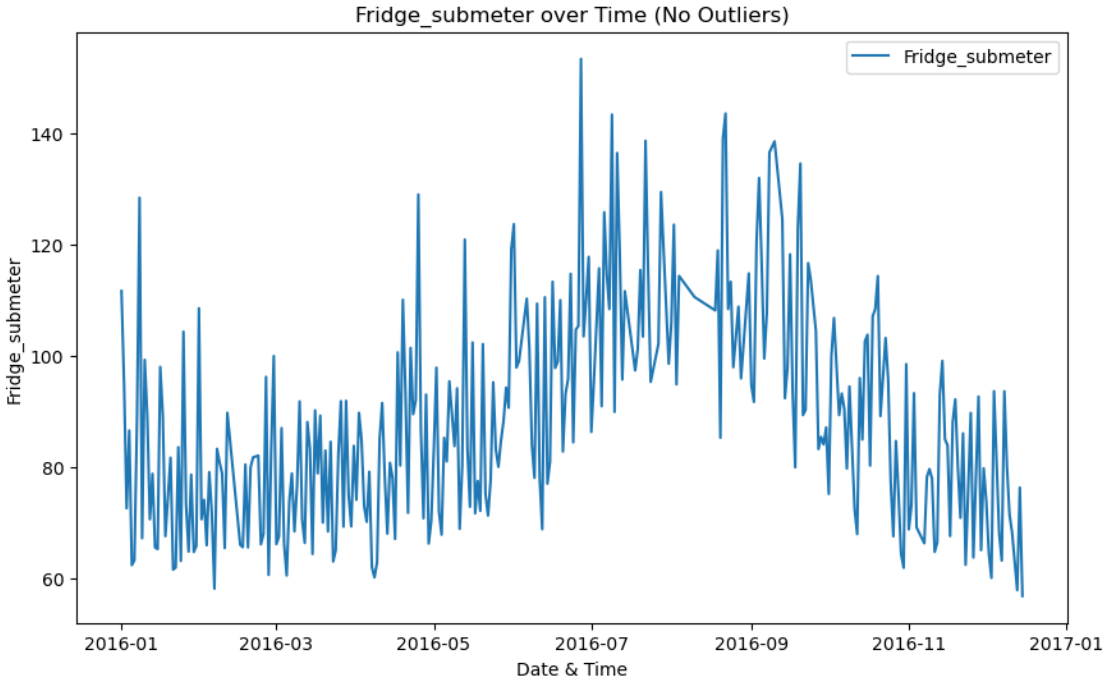


Figure A.2: Fridge power consumption

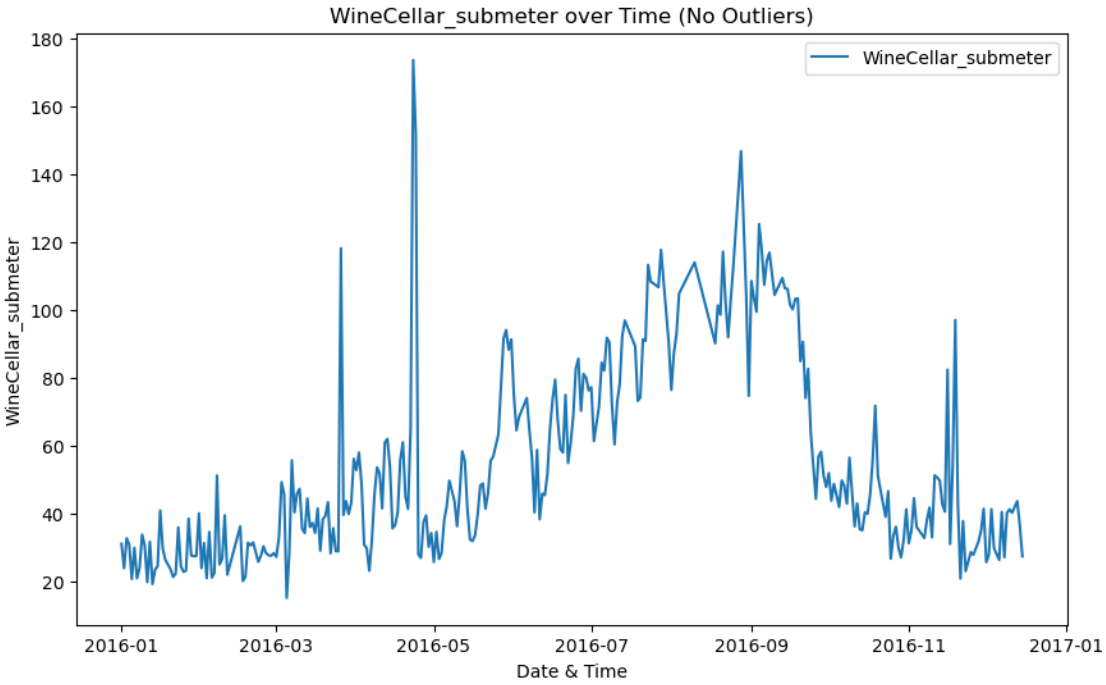


Figure A.3: Wine cellar power consumption

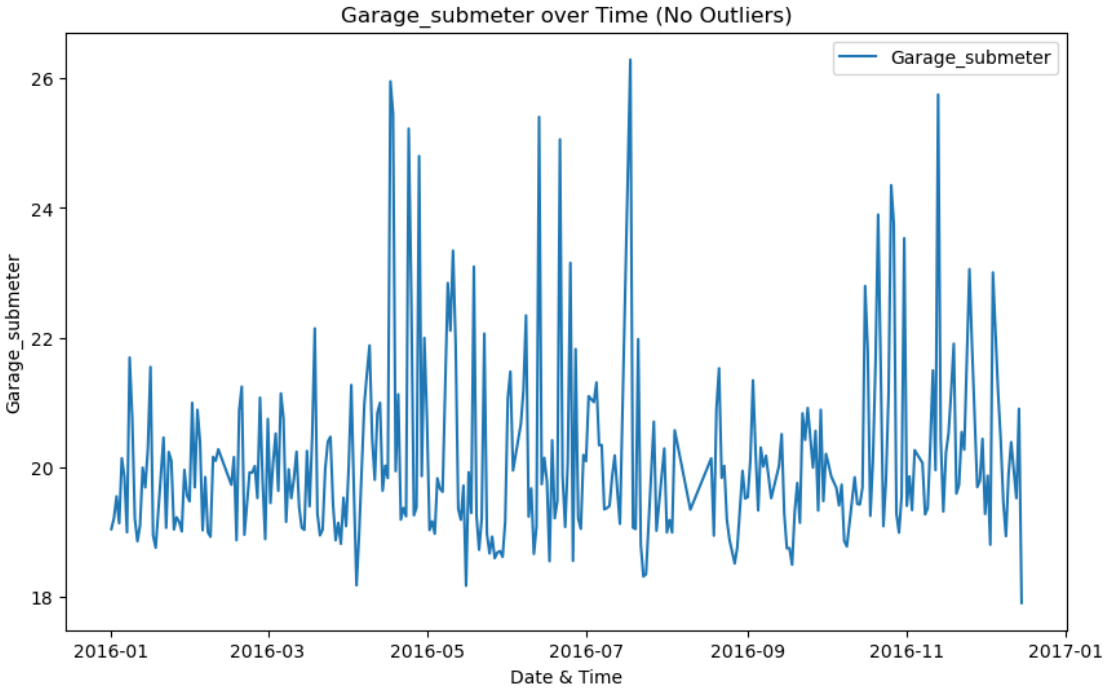


Figure A.4: Garage power consumption

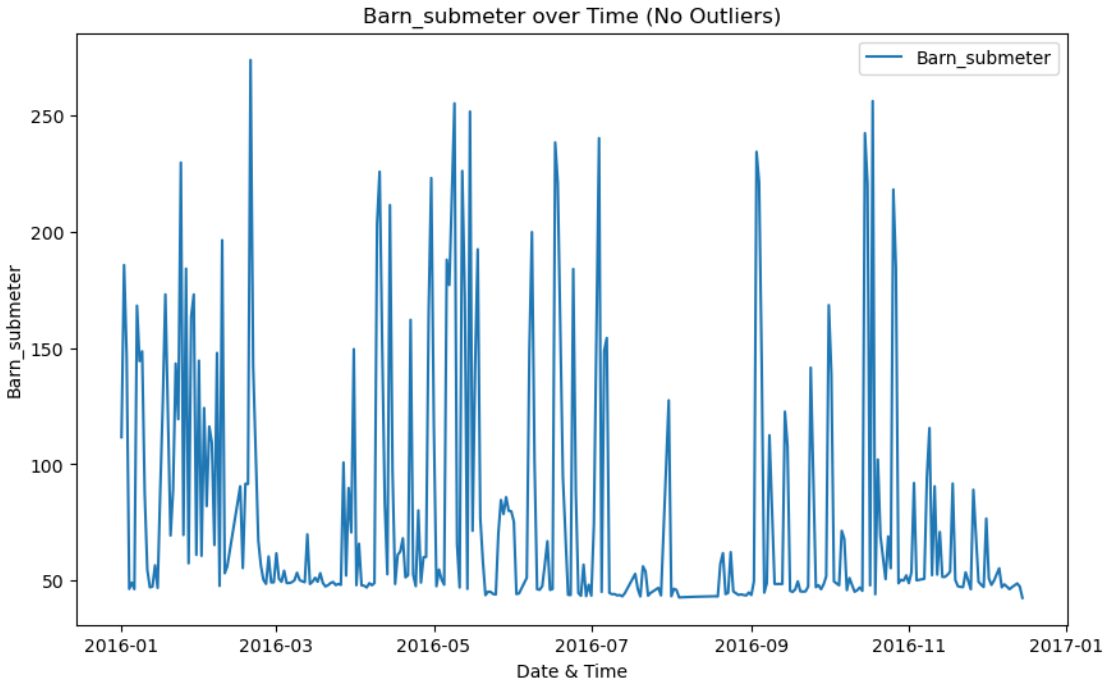


Figure A.5: Barn power consumption

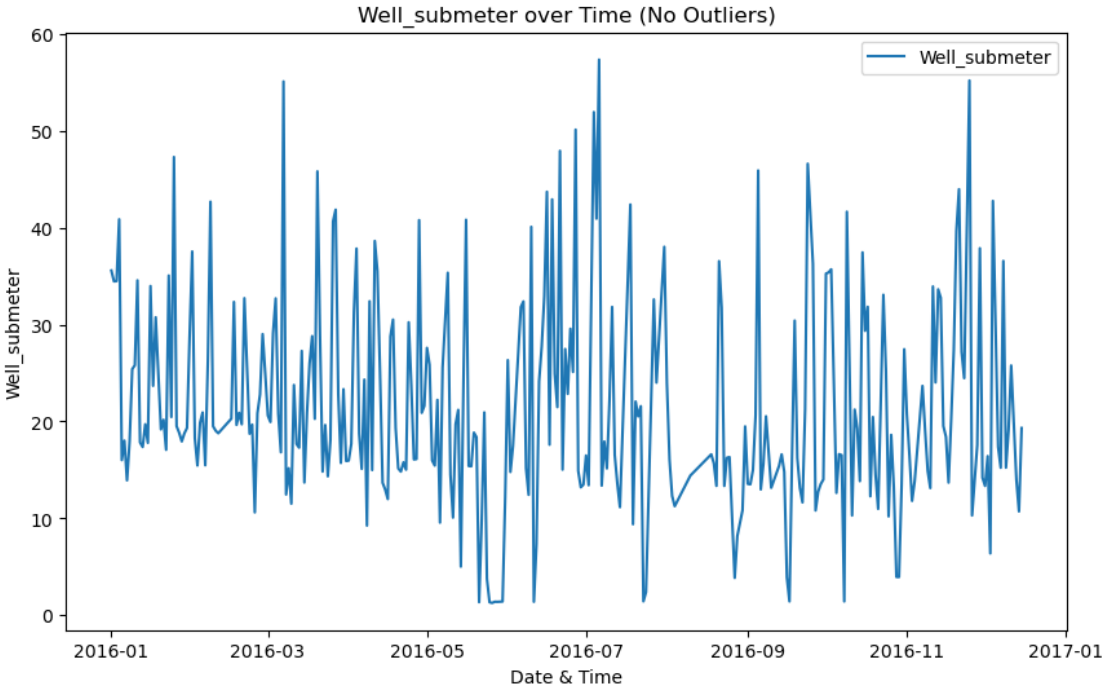


Figure A.6: Well power consumption

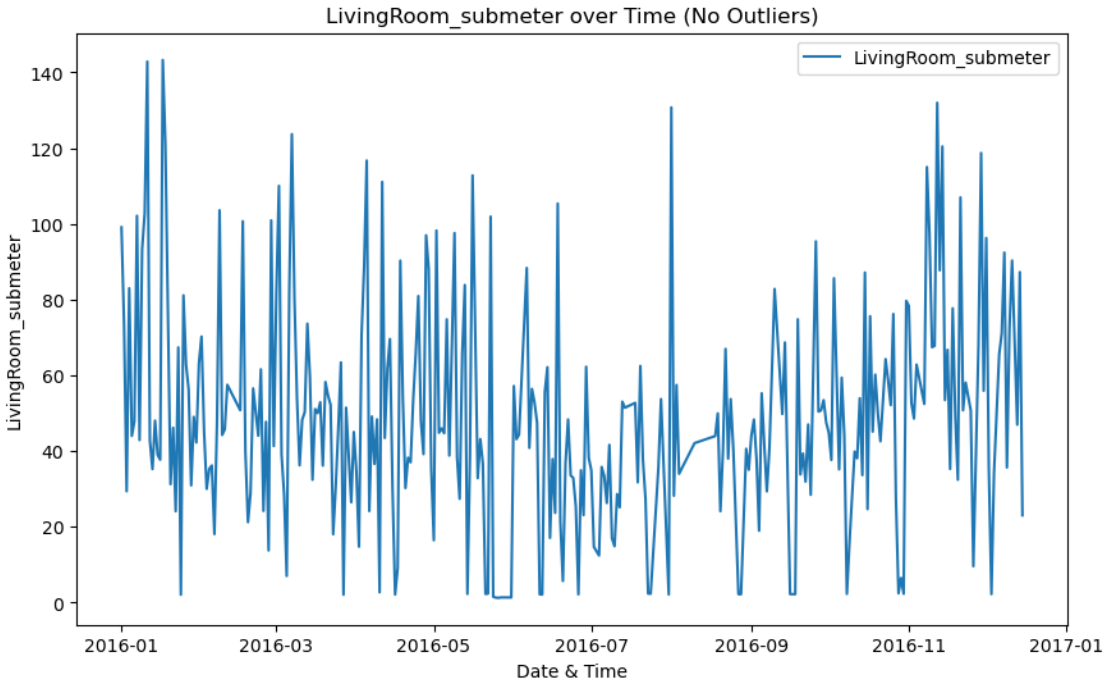


Figure A.7: Living room power consumption

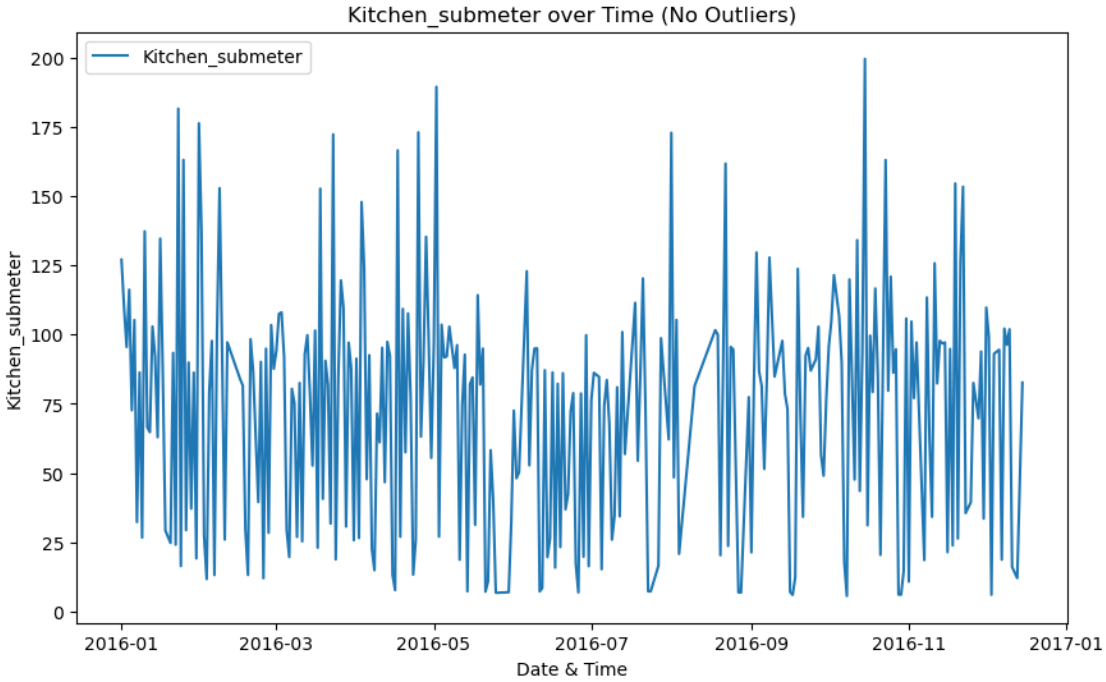


Figure A.8: Kitchen power consumption

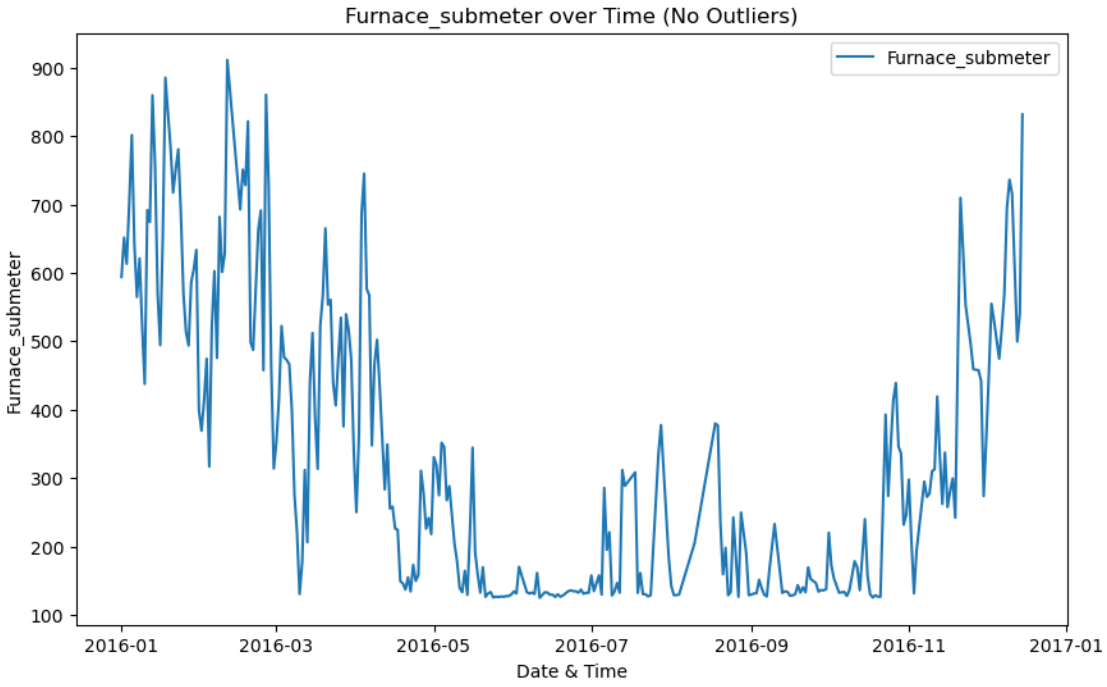


Figure A.9: Furnace power consumption

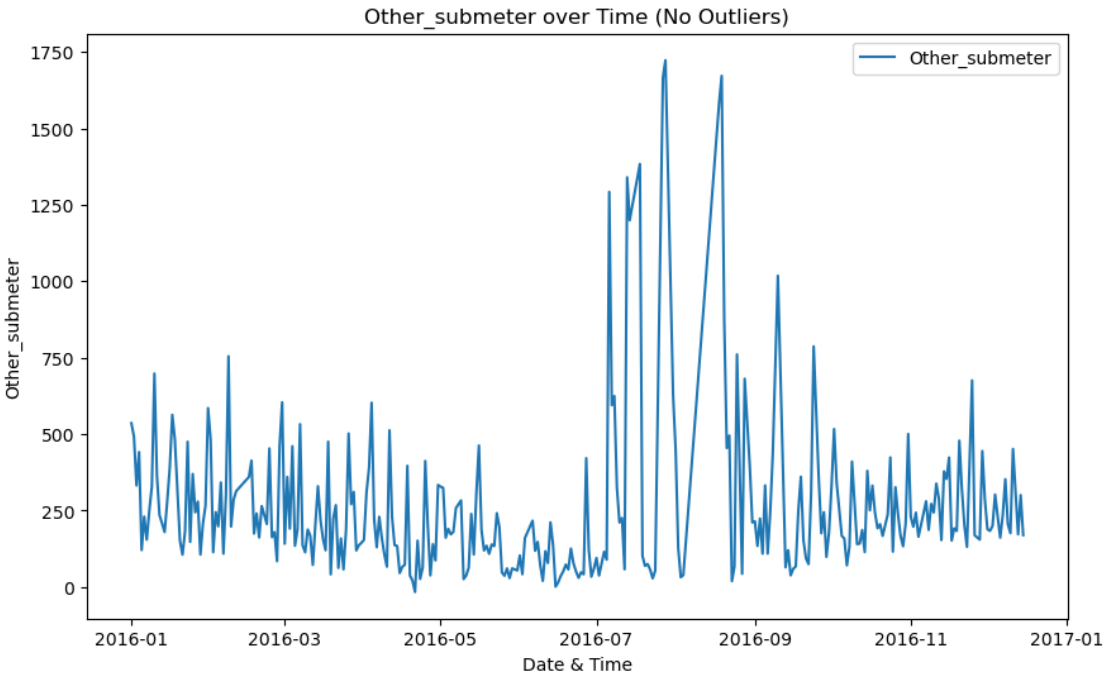


Figure A.10: Other power consumption

The code below, developed by the author, demonstrates the injection of outliers and Gaussian noise [11][73].

‘

```
...
# Define different levels of outlier severity
mild_outliers = np.random.normal(mean_value, std_dev * 2, len(df) // 4)  # Mild: 2 std
moderate_outliers = np.random.normal(mean_value, std_dev * 4, len(df) // 6)  # Moderate: 3 to 4 std
extreme_outliers = [0, min_value * 0.5, max_value * 1.5]  # Extreme: Fixed extreme cases

# Combine all outlier possibilities
outlier_values = np.concatenate([ moderate_outliers, extreme_outliers])

# Function to inject exact percentages of outliers
def inject_outliers(df, outlier_ratio):
    df_outliers = df.copy()
    total_rows = len(df)
    num_outliers = int(total_rows * outlier_ratio)
    num_normals = total_rows - num_outliers

    # Select random indices for outliers
    outlier_indices = np.random.choice(df.index, num_outliers, replace=False)

    # Assign outlier values randomly
    df_outliers.loc[outlier_indices, 'House overall [kW]'] = np.random.choice(outlier_values, num_outli

    # Validate class balance
    actual_outlier_ratio = df_outliers['House overall [kW]'].isin(outlier_values).sum() / total_rows
    print(f"Injected Outlier Ratio: {actual_outlier_ratio:.2%} (Expected: {outlier_ratio:.2%})")

    return df_outliers

# Create dataframes with exact outlier ratios
df_25 = inject_outliers(df, 0.25)
df_50 = inject_outliers(df, 0.5)
df_75 = inject_outliers(df, 0.75)

# Validate the number of outliers injected
df_25_outliers = df_25['House overall [kW]'].isin(outlier_values).sum()
df_50_outliers = df_50['House overall [kW]'].isin(outlier_values).sum()
df_75_outliers = df_75['House overall [kW]'].isin(outlier_values).sum()

df_25.shape, df_50.shape, df_75.shape, df_25_outliers, df_50_outliers, df_75_outliers
...
```

A.2 Web Application Interface and Functionality

This section provides a detailed explanation of the web application developed using Flask, highlighting its key features and functionalities. The application is designed to analyse electricity usage data, detect potential electricity theft, and provide a user-friendly interface for data processing and visualisation.

A.2.1 User Authentication System

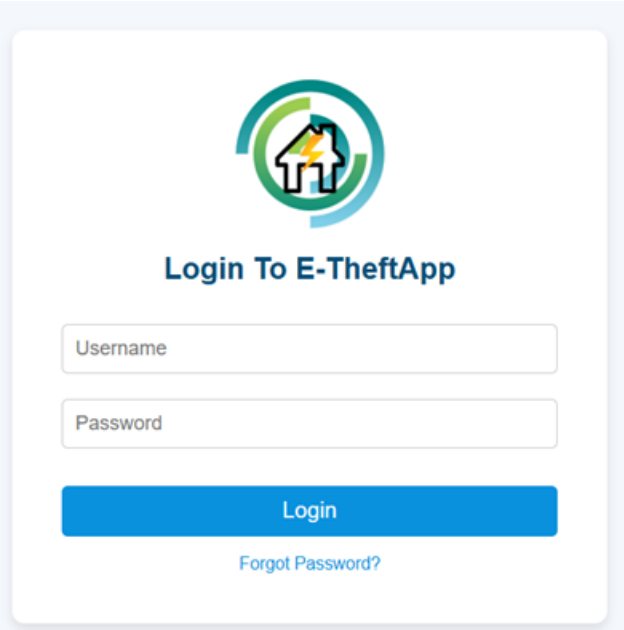


Figure A.11: A snapshot of the login page of the application

The application incorporates a simple user authentication system to ensure secure access and that only authorised personnel can perform data analysis as indicated above in Figure A.11 The */login* route handles user authentication, requiring an admin username and password. Upon successful login, the user is redirected to the main dashboard */index*, where they can interact with the application's features. A logout function */logout* is also available, allowing users to securely end their session.

A.2.2 The Main Analytics Dashboard

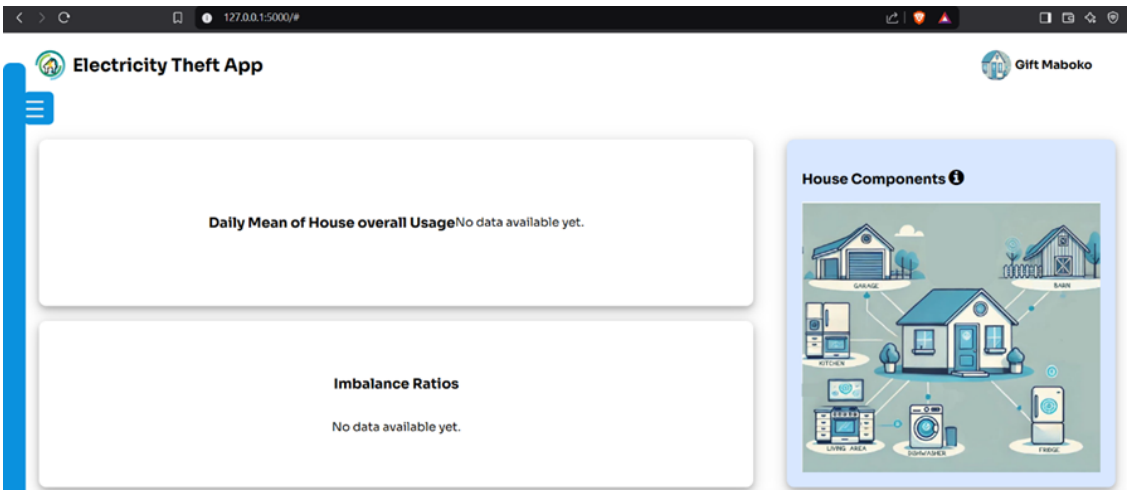


Figure A.12: The Home Page upon successful login

The Home page as seen in Figure A.12 is the central hub of the application, offering a user-friendly interface where all primary functions are easily accessible. Upon logging in, users are greeted with a dashboard displaying key insights, including electricity consumption trends and detection results. This page also provides the option to upload datasets, making it the starting point for data analysis. By integrating both data submission and visualisation, the dashboard ensures users can interact with the system efficiently, gaining real-time insights into electricity usage patterns.

Navigation Bar Features and Functionality

The web application's navigation bar serves as the primary control panel, allowing users to navigate seamlessly between various features. Each item in the navigation bar is designed for accessibility, ensuring that users can efficiently interact with the system. Below is a breakdown of its key components:

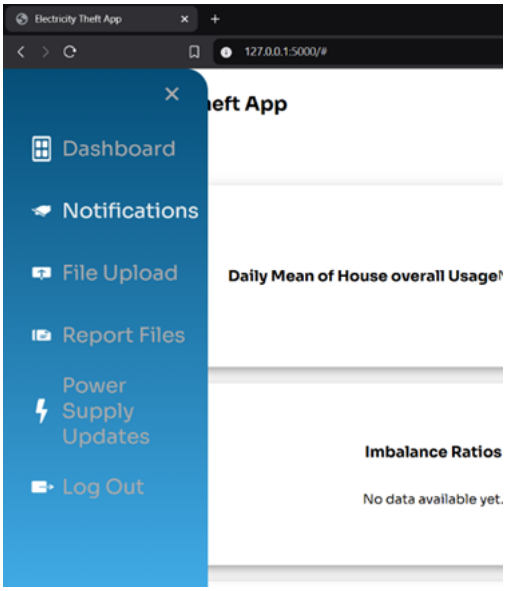


Figure A.13: Side Navigation bar with key features

The key features on the navigation bar in Figure A.13 above, are firstly the dashboard icon which helps redirect the user back to the Home page to view and access the rest of the landing page features. The Notifications feature keeps the authorised personnel informed about important system updates and actions. Whether it's a successful file upload, an error during processing, or the completion of an analysis, notifications provide real-time feedback to guide users through each step. The features enhance user awareness of energy usage patterns and prompt further investigation for when there are unusual consumption spikes and high-risk timeframes of theft identified.

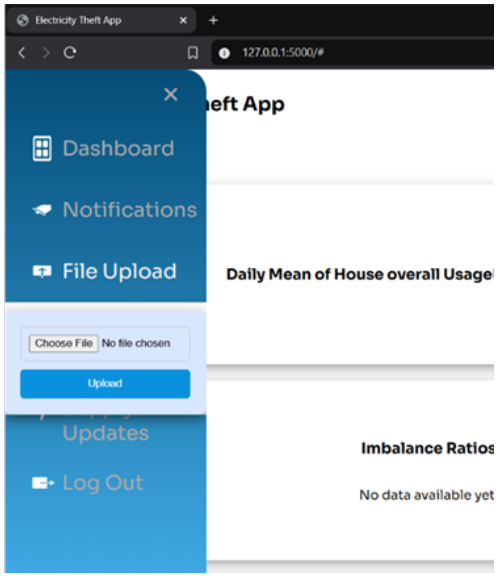


Figure A.14: Side Navigation bar with key features

The core feature on the navigation bar is the File Upload icon, which has a dropdown that reveals a file upload function, uploading for the input energy dataset as a csv file, this is shown in Figure A.14 Upon pressing the "Upload" button, the backend data preprocessing, analysis and model predictions are initiated. Once the system has analysed a dataset, users have the option to download a detailed report of the findings using the "Report Files" feature. The processed file includes timestamps, recorded electricity usage, and classifications indicating whether theft was detected. This functionality allows for further analysis or record-keeping, giving users control over their data in a structured format.

There's also a "Power Supply Updates" feature that keeps users informed about whether the system is using electricity from the main power grid or a backup source. This helps in monitoring power reliability and detecting potential irregularities in consumption. When the main supply is active, the interface reflects normal operation, but if the system switches to a backup source such as a generator or battery the status updates accordingly (to be fully implemented). This feature is particularly useful for tracking grid stability and understanding how often alternative power is used. It also plays a role in theft detection, as unusual power usage during backup supply could indicate unauthorised consumption. By providing real-time visibility into power sources, this feature helps users manage their energy more efficiently and stay prepared for outages. Lastly, is the "Logout" function for security and session management, allowing users to safely exit the system. Once selected, it ends the current session and redirects the user to the login page, ensuring that unauthorised access is prevented by requiring authentication for each session, to maintain data privacy and system integrity of the app.

A.2.3 Data Visualisation and Insights

This section provides users with clear, easy-to-read graphs that highlight daily power usage and the classification of detected cases after the uploaded input data has been processed. The visual approach helps users seamlessly spot patterns or anomalies, offering a deeper understanding of their electricity data. To enhance interpretability, the web application includes two key visualisation features.

Daily Mean of House Overall Electricity Usage

By plotting the daily mean electricity usage on a time-series graph, users can quickly identify patterns and spot any unusual fluctuations in their energy consumption. This feature is useful for detecting inconsistencies that might indicate inefficiencies, faulty appliances, or even unauthorised usage. With an intuitive graphical

representation in Figure A.15, users can easily interpret long-term trends, making energy monitoring more accessible and actionable.

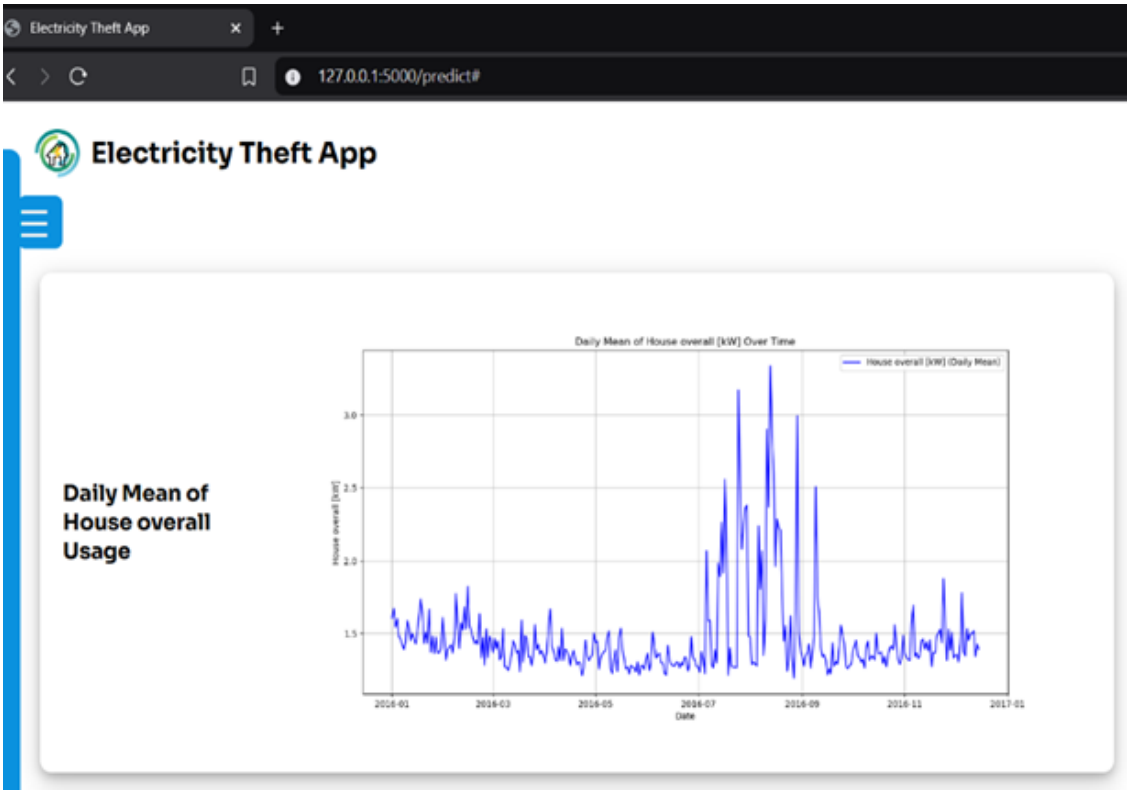


Figure A.15: Daily Mean of House Overall Electricity Usage graph

Class Distribution of Predictions

The feature ensures transparency in how the system classifies electricity usage behaviour. By generating a bar chart that compares the number of theft and non-theft cases detected, users gain insight into the prediction outcomes of the model. This visualisation helps highlight whether the dataset is balanced or if theft cases are disproportionately occurring. Understanding this distribution depicted in Figure A.15 allows users to assess the reliability of the predictions and take appropriate action based on the model's findings.



Figure A.16: Class Distribution of Electricity Theft Predictions

A.2.4 Data Insights and Predictions

After processing, the application generates an output CSV file "TheftCasesOutput.csv", which contains the original data along with the assigned "Status" labels. The downloading functionality provides a structured CSV file containing timestamps, power usage, and detected theft statuses. This allows offline review of detected electricity theft cases, and the structured data supports further analysis. Figure A.17 shows the insights gained when the csv file was opened in a data wrangler.

The web application provides an intuitive and structured workflow for detecting electricity theft using machine learning. By integrating user authentication, data visualisation, and downloadable reports, the system ensures usability and security while maintaining transparency in its predictions. This implementation demonstrates the effectiveness of AI-driven analytics in identifying fraudulent electricity consumption patterns, offering a valuable tool for energy management and fraud detection.

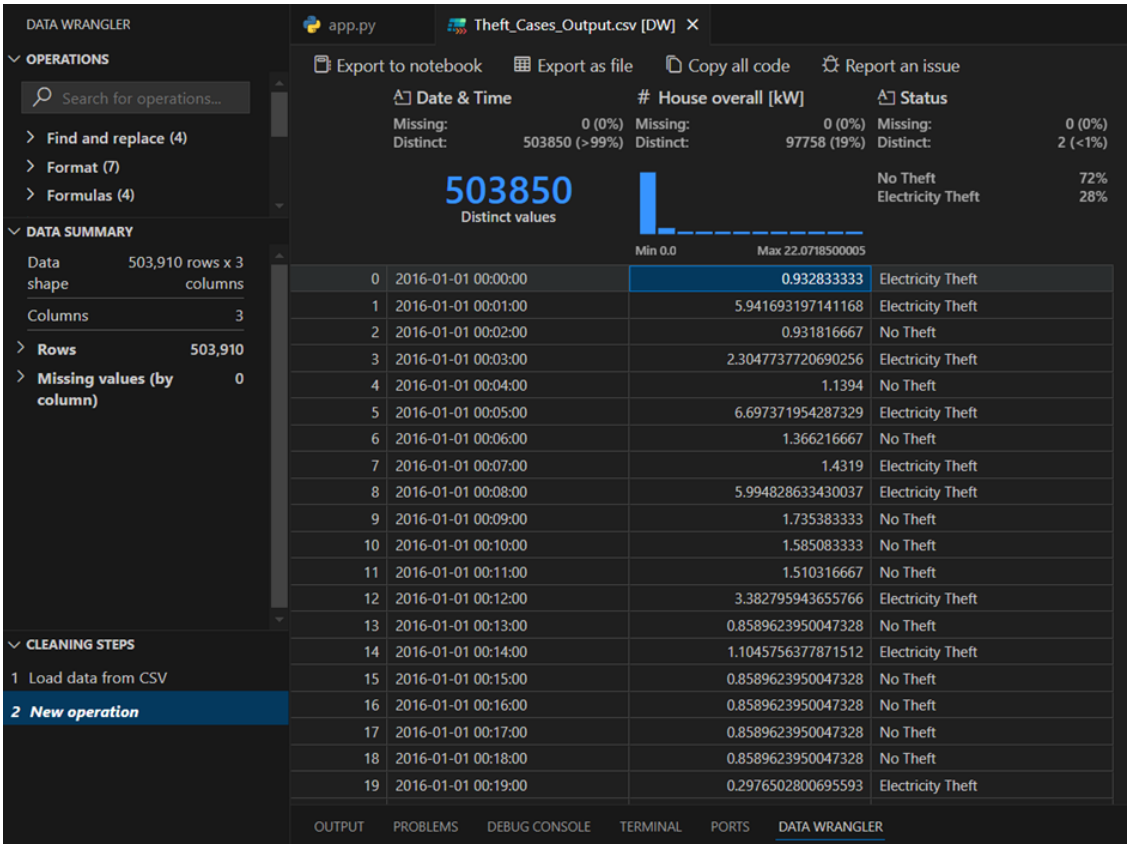


Figure A.17: Theft cases output csv opened in a data wrangler

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