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The Development of a Smartphone Application for Water Monitoring in South Africa Using Machine Learning Techniques

By

Sanet Witbooi

A dissertation submitted in fulfilment of the requirements for the degree of

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In the

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Declaration

I, Sanet Witbooi, student number 1438843 declare that this dissertation is my own unaided work. It is being submitted to the Master of Science in Engineering to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other University.



……..
(Signature of Candidate)

06 …… day of ……May……...….. year……2025……..

Abstract

Water quality monitoring is crucial in South Africa, where water scarcity and pollution present significant public health and environmental challenges. Current monitoring methods are costly, slow, and inaccessible to rural and underserved communities. This study investigates the development of a smartphone application that uses machine learning and computer vision to perform real-time, automated analysis of water quality test strips. The application focuses on six key chemical parameters: pH, total chlorine, free chlorine, total hardness, total alkalinity, and bromine, adhering to South African National Standards. By integrating convolutional neural networks into water quality monitoring, this research addresses the gap in accessible, low-cost solutions.

The research employed a supervised learning approach, developing a CNN-based model trained on a dataset of water test strip images collected under diverse environmental conditions. Data pre-processing techniques such as glare removal and brightness adjustments were applied to enhance model robustness. Experimental testing was conducted in ideal conditions (laboratory settings) and non-ideal conditions. Evaluation metrics included accuracy, F1 score, and recall, with thresholds set at 90% for ideal conditions and 80% for non-ideal conditions. User testing assessed the application's usability and adaptability.

The CNN model achieved an accuracy of 92.5% in ideal conditions and 84.7% in non-ideal conditions, demonstrating its effectiveness in diverse scenarios. Key results indicated that pH and chlorine were the most accurately detected parameters, with mean squared errors of less than 0.05. User feedback highlighted the application's ease of use, with over 85% of participants reporting satisfaction with the app interface and instructions.

Findings underscore the potential of AI-driven solutions to revolutionise water quality monitoring in South Africa. The system's performance exceeds the minimum requirements for practical deployment, though challenges such as lighting conditions and test strip variability remain. The study aligns with global trends in sustainable water management, advocating for community-driven solutions that leverage citizen science. Recommendations include scaling the application to include additional parameters, integrating geotagging features, and enhancing user training modules.

This research presents a novel, accessible tool for water quality monitoring, bridging the gap between advanced technology and real-world application in resource-limited settings. The smartphone application offers a scalable model that can empower communities, improve public health outcomes, and contribute to South Africa's sustainable development goals. Future work should focus on expanding the dataset, improving model generalisability, and exploring partnerships for widespread implementation.

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Nomenclature

AI: Artificial Intelligence

ANN: Artificial Neural Network – A computational model inspired by the human brain, used in machine learning and deep learning applications

API: Application Programming Interface

BGR: Blue-Green-Red – An alternative colour model to RGB, used in OpenCV, where the channels are ordered as Blue, Green, and Red instead of Red, Green, and Blue

CNN: Convolutional Neural Network

COVID-19: Coronavirus Disease 2019 – A global pandemic caused by the SARS-CoV-2 virus

CSIR: Council for Scientific and Industrial Research – A leading scientific and technology research organisation in South Africa

CSPDarknet53: Cross-Stage Partial Darknet 53 – A neural network architecture used in YOLOv4 for feature extraction

CV: Computer Vision – Also referred to as machine vision; it involves enabling machines to interpret and process visual data from the real world

DFL: Distribution Focal Loss – A variant of focal loss designed to improve object detection performance by addressing class imbalance

DWA: DWA: Department of Water Affairs, a South African government body, was tasked with managing and protecting water resources

EXIF: Exchangeable Image File Format – A standard that specifies the metadata of an image, such as camera settings, location (if GPS-enabled), and timestamps

F1 Score: The Harmonic Mean of Precision and Recall, providing a single metric that balances the trade-off between the two, making it particularly useful for evaluating a model's performance on imbalanced datasets

GIS: Geographic Information System

GPS: Global Positioning System

HTTPS: Hypertext Transfer Protocol Secure

HSV: Hue, Saturation, Value – A colour model used in image analysis, often more intuitive for colour-based tasks than RGB or BGR

IDE: Integrated Development Environment

ISO: International Organization for Standardization – An international standard-setting body that develops and publishes standards for various industries

IoU: Intersection over Union – This metric calculates the overlap between two bounding boxes. A threshold, typically 0.5, determines whether the lower-confidence box is discarded, reducing false positives

KNN: K-nearest neighbours – A supervised machine learning algorithm used for classification and regression tasks

LAB: A colour model representing lightness (L) and chromaticity (A, B), commonly used for accurate colour representation

LS-SVM: Least-Squares Support Vector Machine

mAP: Mean Average Precision – mAP@0.5 evaluates performance at a moderate overlap threshold of 50% (IoU=0.5). mAP@0.5-0.95 averages precision across stricter IoU thresholds, typically from 0.5 to 0.95 in increments of 0.05. This metric evaluates localisation and detection accuracy under varied criteria

ML: Machine Learning

NMS: Non-Maximum Suppression – A technique used in object detection to reduce duplicate bounding boxes by keeping only the box with the highest confidence score for each detected object

NMMP: National Microbial Monitoring Programme – A programme monitoring faecal contamination in surface water to assess health risks

NWA: National Water Act – South Africa's primary legislation governing water resource management

NRW: Non-Revenue Water – Water that is produced but not billed, often due to leaks or theft

OpenCV: Open-Source Computer Vision Library – A popular library for image and video processing, often used in machine learning and computer vision applications

OpenPose: A library for real-time pose estimation and multi-person keypoint detection

OUTA: Organisation Undoing Tax Abuse – A South African non-profit organisation focused on governance and accountability

PADs: Paper-Based Analytical Devices – Simple, portable tools used for chemical analysis in resource-limited settings

PANet: Path Aggregation Network – A neural network component used in YOLOv4 for feature pyramid networks

PII: Personally Identifiable Information

PIL: Python Imaging Library – A Python library used for opening, manipulating, and saving image files

POPIA: Protection of Personal Information Act – A South African law regulating data protection and privacy

REMP: The River Eco-status Monitoring Programme – A programme that monitors the ecological health of South African water resources

RESTful: Representational State Transfer – An architectural style for designing networked applications based on stateless communication

RGB: Red-Green-Blue – A colour model in which colours are represented as a combination of red, green, and blue light intensities

RHP: River Health Programme – A South African initiative monitoring the ecological status of rivers

RNNs: Recurrent Neural Networks – A type of neural network designed for sequential data, often used in natural language processing

SA: South Africa

SAWQ: South African Agricultural-Water-Quality – Guidelines for assessing water quality for agricultural purposes

SANS: South African National Standards

SAR: Sodium Adsorption Ratio – A measure of water's suitability for irrigation based on sodium content

SEMA: Specific Environmental Management Acts – Legislation addressing environmental issues in South Africa

SQL: Structured Query Language – A standardised programming language used for managing and manipulating relational databases

SSD: Single-Shot Detectors – A neural network-based object detection algorithm

SVM: Support Vector Machine – A supervised learning algorithm used for classification and regression

TensorFlow: An open-source machine learning platform developed by Google

UAT: User Acceptance Testing

UI: User Interface

UID: Unique Identifier – The unique user ID assigned to an app user in the Firebase database

UNU-WIDER: United Nations University World Institute for Development Economics Research

USAID: United States Agency for International Development

UX: User Experience

WQI: Water Quality Index

WRC: Water Research Commission

YOLO: You Only Look Once – A real-time object detection system based on convolutional neural networks. This system or model is also referred to as YOLOv8, including the version number, and YOLOv8n, including the version number and model size, in this report

Chapter 1: Introduction

1 Introduction

Water quality assessment is fundamental to environmental science and public health management. This is especially so for a water-stressed country like South Africa, where challenges to clean drinking water are prevalent. This assessment encompasses the evaluation of physical, chemical, and biological parameters such as turbidity, pH levels, organic and inorganic chemicals, and nutrient levels [1]. According to Bartram and Ballance [2], water quality monitoring is essential for identifying potential risks posed by contaminants and pollutants, guiding regulatory decisions, and implementing effective pollution control measures. The World Health Organization (WHO) recognises clean drinking water as a basic human right, emphasising the global importance of water quality assessment [3].

In the context of Africa, and more particularly South Africa, water quality assessments are essential for understanding the challenges in providing clean and safe drinking water to citizens. The quality of drinking water sources is on the decline as a result of activities aimed at development in growing nations [4], which include rapid economic expansion, urbanisation, and ongoing chronic pollution [5]. Both point and diffuse sources are in jeopardy as a result of organic pollutants from failing domestic sewage treatment plants, storm runoffs, and damaged septic tanks. Inorganic fertilisers often lead to an imbalance of nutrients and the contamination of groundwater [4]. In addition, reports from the Department of Water and Sanitation highlight critical conditions in the country's water systems, necessitating the implementation of reliable water quality monitoring (WQM) strategies [3, 6].

The legal frameworks governing water quality assessment, both globally and locally, play a role in ensuring compliance with standards and regulations. The National Water Act of 1998, alongside Specific Environmental Management Acts (SEMA) such as the National Water Act 36 of 1998 (NWA) and the Water Services Act 108 of 1998 (WSA), provide guidelines for managing water resources sustainably and safeguarding water quality [7]. These laws mandate the monitoring of chemical, physical, and biological characteristics of water bodies to improve water quality and to ensure continuous monitoring, in line with the WHO guidelines [8].

Understanding the legal aspects of water quality assessment sets the foundation for exploring the intersection between environmental monitoring and advanced technologies such as artificial intelligence, computer vision, and machine learning (ML). These technologies enable the automation of data collection, data analysis, pattern recognition, and predictive modelling to enhance resource monitoring systems' efficiency [9]. Rolfe [10] elaborates on this phenomenon through a discussion of how machine learning techniques enable real-time data processing, anomaly detection, and decision support in environmental monitoring applications. In the context of water quality monitoring, computer vision algorithms can analyse images of water samples, detect colourimetric changes in test strips - as with this investigation - and quantify water quality parameters with precision. This allows for more proactive, data-driven responses to environmental challenges [4]. By integrating computer vision algorithms, such as those used in visual object detection, with water quality assessment, the efficiency of automated colourimetric analysis on water test strips can be evaluated with both qualitative and quantitative metrics.

2 Overview of the Research Problem

In response to growing concerns around environmental sustainability and water resource management, this project centers on a technologically advanced solution designed for water quality monitoring. The development of a mobile application with an integrated web application and database, to support real-time environmental monitoring, this system specifically targets and aims to fill the gap created by the lack of real-time water quality data across South Africa. The application is driven by a machine learning and computer vision (CV)-based algorithm that determines the safety of a drinking water sample by

automating colourimetric analysis. By addressing key gaps in current water monitoring technology, this project aims to improve management practices and introduce innovative methodologies that mitigate issues of water scarcity and quality degradation. This project also provides a tool for water monitoring and advances the technological framework for tackling emerging environmental challenges, aligning with global efforts to preserve water resources amidst escalating demand and environmental stressors.

This research addresses the need for accessible water quality monitoring by developing artificial intelligence (AI)-driven methods using a South African context by evaluating local environmental and infrastructural challenges to provide a proof of concept.

2.1 Context and Background

Water quality monitoring is essential to environmental science and public health, particularly in areas where water scarcity and pollution threaten ecosystems and human well-being. In South Africa, these challenges are acute due to rapid urbanisation, industrial growth, and historic inequalities in infrastructure, which have led to degraded water quality in many regions. In light of the global push towards accessible clean drinking water, as outlined by the WHO [3], the fact that many South African communities, especially in rural and peri-urban areas, still struggle to obtain safe drinking water on a daily basis due to contamination and inadequate monitoring, depicts the urgency of this technology.

Traditionally, water quality monitoring in South Africa has been resource-intensive, often requiring specialised skills and costly equipment. This dependency limits accessibility and effectiveness, especially for underserved communities vulnerable to waterborne diseases. Legislative frameworks, including the National Water Act of 1998 and SANS 241 guidelines; set safety standards for water; however, infrastructure and financial constraints at the municipal level have hindered compliance.

Recent advances in machine learning and computer vision offer promising solutions to these issues. AI-driven approaches can enhance water monitoring through real-time data analysis and pattern recognition, enabling quicker, more accurate assessments. Technologies like convolutional neural networks (CNNs) allow for automated visual analysis of test strips, potentially making monitoring more accessible while empowering communities to actively engage in water safety efforts.

2.2 Significance of the Issue

Poor water quality threatens biodiversity, exacerbates pollution in ecosystems, and adversely impacts agricultural productivity and community health. High rates of waterborne diseases in rural areas underscore the need for scalable, accessible monitoring solutions, not only in South Africa. Globally, sustainable water management is increasingly crucial, particularly in regions vulnerable to climate change and water scarcity. The nation, grappling with both quality and quantity issues, stands to benefit from innovative technologies that address gaps in water infrastructure. However, current monitoring practices often lack the timeliness needed for effective intervention, highlighting a critical knowledge gap that this study seeks to address.

3 Statement of the Research Problem – Identifying the Gap and Research Focus

Traditional water quality assessment methods have not met the diverse needs of South African communities, particularly in rural and peri-urban areas where contamination risks are heightened. These methods are constrained by high costs, complexity, and the need for specialised equipment, making them unsuitable for widespread use in underserved regions. Moreover, they lack the ability to provide

real-time insights essential for prompt action. Although frameworks such as the National Water Act and SANS 241 standards provide guidelines, implementation gaps leave communities vulnerable to waterborne diseases and other health risks.

A significant portion of the population also lacks the necessary educational background to interpret water quality readings, understand which parameters are critical, or assess their implications. This challenge is especially pronounced in rural communities that rely on untreated natural water sources, further exacerbating the risks associated with poor water quality. Without accessible monitoring solutions, these communities remain at risk of consuming unsafe water.

Emerging technologies such as machine learning and artificial intelligence offer potential solutions to these challenges, yet few implementations address the practical constraints of resource-limited settings. This study, therefore, aims to develop an AI-based water monitoring system capable of real-time analysis under varied environmental conditions. The proposed solution is low-cost, scalable, and designed with a shallow learning curve, ensuring accessibility for individuals with diverse socio-economic backgrounds and levels of education. By aligning with national water safety standards, this system addresses urgent public health needs while enhancing community resilience to water quality issues.

4 Purpose of the Research

The primary objective of this research is to design and validate an AI-based water monitoring application suited to the specific needs of South African communities. This project addresses a focused issue within the broader water quality crisis: the need for an accessible, low-cost tool that provides accurate, real-time data to end-users, from citizens to health officials. By employing a machine learning model for visual analysis of test strips, this research empowers communities to play an active role in ensuring their own water safety.

4.1 Addressing Limitations in Existing Research

Existing research has often overlooked the challenges posed by limited infrastructure and resources in underserved South African communities. Current AI models for water monitoring typically rely on stable power, high-quality cameras, and advanced infrastructure, limiting their applicability. Laboratory-based models show promise under controlled conditions but have not been rigorously tested in field conditions. This study aims to fill these gaps by developing a system that adjusts to environmental variability and delivers results under less-than-ideal conditions.

5 Contribution of the Study

This research makes both theoretical and practical contributions. Theoretically, it challenges the reliance on traditional, equipment-intensive water quality assessment by introducing a CNN-based model capable of real-time analysis. It presents a new framework that leverages mobile technology and citizen science for decentralised water monitoring – especially relevant in regions like South Africa, where resource constraints limit access to conventional methods. Additionally, by demonstrating the application of machine learning to environmental monitoring under variable conditions, this study extends existing theories on AI's role in real-world, resource-constrained settings.

Practically, this study advances water quality monitoring by developing a machine learning application tailored to South African conditions. The AI-driven system has the potential to become a crucial tool for communities, empowering them to monitor water safety independently, without the need for costly

infrastructure or specialised skills. By offering a scalable, practical model for real-time monitoring, this research supports South Africa's sustainable development goals and contributes to the global discourse on environmental health and public safety.

6 Research Questions and Objectives

The research questions and objectives of this study are designed to guide the development and evaluation of an AI-based water quality monitoring system tailored to South African needs.

6.1 Primary Research Question

The primary research question driving this study is: To what extent can a water monitoring application, leveraging machine learning techniques and convolutional neural networks, accurately evaluate and categorise real-time water quality parameters, including pH, chlorine, and hardness? These key parameters also referred to as chemical indicators – focus on the chemical makeup of the water profile – ensuring its safety, potability, and compliance with health standards. This aligns with the broader issues identified earlier, addressing the need for accessible and accurate monitoring solutions tailored to South Africa. As water safety remains a pressing public health issue, this research will assess how AI-based image analysis can improve water quality assessments for South African communities, even under resource-constrained conditions.

6.2 Supporting Research Questions and Objectives

The key supporting research question – which is also referred to as a secondary or sub-research question in this report – that provides a quantitative aspect to support the primary research questions is: What minimum averaged performance metrics should be obtained by the trained model in classifying water quality parameters to ensure 90% accuracy in ideal conditions and 80% accuracy in non-ideal conditions? In addition, to assess the efficacy of the development process and the outcome of the software elements that support the machine learning object detective and colour classification, the supplementary questions listed below will also be considered. These questions are not explicitly answered or reported on in the research report but need to be addressed before the secondary or primary research questions can be answered, from both a qualitative and quantitative perspective. These questions are as follows:

1. How accurately can the model classify chemical indicators of water quality based on test strip images taken in diverse environmental conditions?
2. To what extent do image pre-processing techniques, including brightness adjustment, and glare removal, improve classification accuracy, and how do they impact overall efficiency?
3. To evaluate the effectiveness of the implementation of this application – which is not assessed in this project due to its scope – it can be determined to what extent the system can be integrated with mobile infrastructure and engage citizens to create a scalable, community-based water monitoring solution.

Each question addresses gaps in the literature and contributes to the advancement of water quality monitoring. Objectives are measurable, with performance indicators such as F1 score thresholds, accuracy rates, and adaptability guiding systematic evaluation of the system's efficacy.

7 Significance of the Research

The research contributes to the theory of water monitoring using AI-driven technologies by challenging traditional equipment-intensive water quality assessments and introducing a CNN-based model for real-time analysis. This model leverages mobile technology and citizen science for decentralised water monitoring, particularly relevant in South Africa, where conventional methods for water quality testing are often inaccessible or too expensive. In practice, the research presents a mobile app that combines image analysis with local data storage and geotagging, creating a scalable, community-driven framework for water quality monitoring.

7.1 Contribution to Theory and Practice

Theoretically, this research challenges the traditional reliance on equipment-intensive water quality assessments by introducing a CNN-based model for real-time analysis. This model leverages mobile technology and citizen science for decentralised water monitoring, particularly relevant for South African regions where conventional methods are inaccessible. By showcasing machine learning in environmental monitoring, this study extends theories on AI applications in resource-limited settings. Practically, the research introduces a mobile app that integrates image analysis with local data storage and geotagging, supporting a scalable, community-focused monitoring framework. This app could inform policy by providing accessible tools for water quality assessments, bridging technological innovation with public health policy.

7.2 Relevance to Current Trends and Future Development

This study aligns with global trends in environmental technology and public health, addressing the need for sustainable water management amid climate change and resource scarcity. In South Africa, where water quality issues are ongoing, this research emphasises equitable access to safe water. By harnessing smartphone technology, the study promotes citizen science and empowers communities in environmental stewardship. Addressing these questions contributes to a broader understanding of sustainable development, aligning with both local and global priorities in water safety and public health.

8 Theoretical Framework - Core Theoretical Underpinnings

This research is grounded in positivist and pragmatic paradigms, aligning with both empirical observation and practical application. The positivist approach prioritises systematic, quantitative methods to assess the system’s technical well-established performance metrics through precision, recall, and F1 scores. This ensures that model performance is evaluated, maintaining objectivity and reliability in monitoring water quality parameters.

To complement the theory-led nature of positivist testing, the pragmatic approach emphasises real-world applicability, prioritising technology deployment in varied and unpredictable settings. Pragmatism is particularly relevant here, as it advocates for user-centred outcomes, including community usability and data accessibility. This framework supports the use of machine learning for practical, user-driven applications in water quality monitoring, ensuring the system’s relevance to South African communities. Together, these perspectives provide a foundation for the system's development and evaluation, maintaining scientific rigour while addressing local, real-world needs.

9 Scope and Delimitations

The scope of this study is defined to address specific regional and technological limitations relevant to South Africa's water monitoring needs. It also considers three key factors in the development of this project: time, cost, and quality. This helped to determine the study's focus, limitations, and assumptions.

9.1 Boundaries of the Research

This study is geographically limited to South Africa, focusing on rural and peri-urban communities where water quality monitoring infrastructure is lacking, to determine what the minimum services need to be to address the identified problem. However, this system can be used across the country wherever internet access is available. The system primarily assesses and is limited to six chemical indicators – total hardness, total chlorine, free chlorine, bromine, total alkalinity, and pH – via the smartphone application designed for accessibility across diverse environmental conditions that then maps these water quality results on a live map hosted by the web application.

From a technical perspective, the study is confined to using CNNs and mobile devices, excluding other machine-learning algorithms or hardware-dependent systems. CNNs, or Convolutional Neural Networks, are a type of artificial intelligence that specializes in analysing visual data, such as images or videos. In this study, they are used to identify patterns in water test strip images, helping to detect specific water quality indicators like pH or chlorine levels. By focusing on mobile devices, the study aims to make this technology accessible and portable, allowing users to test water quality directly from their phones. The image analysis framework interprets test strip colours and does not identify contaminants beyond the specified parameters and cannot give any commentary on the quality or viability of the physical test strip being used or its ability to effectively perform the chemistry resulting in the observed colour change. Data collection is limited to images of the test strip and is collected from May 2023 to November 2024, though future research may examine seasonal adaptability.

9.2 Development Assumptions and Limitations

The study assumes users have access to smartphones and basic internet connectivity, though these may vary across communities. Additionally, it is assumed that the colour-based chemical indicators accurately reflect water composition, with SANS 241 standards providing the foundation for water safety metrics. The system also relies on user compliance and assumes that the user will use the system as intended, but accepts that mistakes may be made when using the mobile application and uploading data to the system.

Limitations include the system's sensitivity to environmental factors, such as lighting and background noise, which may impact image quality. However, focusing on smartphone technology and test strip analysis allows an in-depth exploration of a scalable, community-driven monitoring solution, contributing valuable insights into low-cost, decentralised water quality assessments for diverse South African contexts. The system only accepts images of the physical test strip and is limited to the instructions provided by the manufacturer on how to use the test strip most effectively. The software used is also limited to that only required to generate a proof of concept. For commercial use of the application, the software and hardware used to develop the system may be upgraded, and implement more costly redundancies that could increase accuracy and user-friendliness.

10 Dissertation Roadmap

This dissertation is organised into six chapters, each systematically investigating the research problem and meeting the study's objectives. The following chapters set out a roadmap that navigates through the project development, system testing, and analysis of experimental results and improvements.

10.1 Chapter 2: Literature Review

This chapter reviews previous research on water quality monitoring, examining the limitations of traditional methods and the role of machine learning and computer vision as innovative solutions. It synthesises findings on CNNs and environmental applications, establishing the theoretical basis for the study and contextualising how this research extends beyond prior studies.

10.2 Chapter 3: Research Methodology

The methodology chapter details the research design, methods, and data collection processes. It describes the application of CNNs and machine learning for image analysis, including model training and the process of collecting and labelling the training data set. Additionally, it covers environmental adaptations, such as brightness adjustment and glare removal, to support consistent monitoring.

10.3 Chapter 4: Experimental Results

This chapter presents quantitative findings, focusing on the AI-based system's performance across various metrics. It evaluates the model's accuracy in detecting chemical indicators, including pH, chlorine, and hardness, in both ideal and challenging conditions. Insights into the system's strengths and areas for improvement are provided, forming the basis for the subsequent discussion, from both a technical and potential user experience perspective.

10.4 Chapter 5: Discussion

This chapter analyses the implications of the findings in the context of the research questions and existing literature, assessing the system's accuracy, and consequences on public health. It also considers study limitations and identifies areas for future research, particularly regarding scalability and community engagement in South Africa.

10.5 Chapter 6: Conclusion

The concluding chapter summarises key findings and their implications for water quality monitoring in South Africa. It revisits the research objectives, evaluates the study's effectiveness, and highlights both theoretical and practical contributions. Recommendations for policymakers, practitioners, and researchers underscore the importance of sustainable, accessible solutions for water quality monitoring.

11 Conclusion

In summary, this introduction establishes the pressing need for accessible water quality monitoring in South Africa, particularly in underserved communities facing health risks due to contaminated water. The study proposes an innovative AI-based system leveraging machine learning and computer vision to provide real-time, cost-effective assessments, filling a critical gap in current methods. By adapting to local conditions, this system aims to empower communities, promote public health, and contribute to sustainable development goals. Through a structured investigation, this dissertation will explore how AI technology can offer practical, scalable solutions to South Africa's water challenges, providing a model for similar contexts globally.

Chapter 2: Literature Review

1 Introduction

Assessing water quality involves evaluating physical, chemical, and biological factors to detect contaminants and manage pollution. Legal frameworks, such as the National Water Act in South Africa, ensure adherence to water quality standards. New technologies like AI, machine learning, and computer vision improve water quality monitoring by automating data collection and analysis, leading to more efficient and proactive responses. These technologies can also enhance the accuracy of colourimetric analysis on water test strips, supporting precise water quality assessments.

This literature review explores the significance of water quality monitoring through the legal frameworks governing it, and the potential of advanced technologies such as AI and CV to enhance monitoring accuracy and efficiency. The primary objective is to evaluate the effectiveness of AI and CV in water quality assessment through colourimetric analysis and You Only Look Once (YOLO)-based object detection on water test strips, with a focus on improving data collection, analysis, and environmental health management. The review also aims to assess the impact of these technologies on citizen science involvement in environmental health management and its potential to address emerging challenges in water resource management and sustainability.

2 The Legal Frameworks: Global and Local Perspective

The development of a water quality monitoring system that determines whether water is safe to consume must meet legal benchmarks. The National Water Act (NWA) 36 of 1998 [11] was instated to manage South Africa's water resources, which led to the creation of the Water Research Commission (WRC). The WRC in turn developed the Water Allocation System, which aids in the management of the allocation and distribution of water resources across the country [7]. Specific Environmental Management Acts (SEMA) such as the NWA 36 of 1998 and the Water Services Act (WSA) 108 of 1998 are the main legislation in South Africa that govern and regulate water laws that relate to water rights. NWA asserts that South Africa's water resources must be safeguarded, managed, and used sustainably. Section 3(1) of the WSA explicitly affirms that all citizens must have access to clean drinking water [7]. This is in line with the World Health Organisation's Guidelines for Drinking Water Quality [12] and influenced the development of the South African Water Quality Guidelines for Domestic Use [13]. These standards will be considered during the software development process.

In accordance, the South African National Standard (SANS) 241 describes the minimum criteria that must be met for drinking water to be deemed safe for human consumption. This criterion examines microbiological, physical, aesthetic, and chemical properties. Water sources that are SANS 241 compliant are considered safe to drink [14]. Hence, the application developed in this study is required to assess the presence of chemical contaminants as indicated by the water test strip within permissible limits defined by the SANS 241 standard. In addition, it also needs to identify contaminants that should not be present in the water that registers at a level above zero mg/L [14].

3 Overview of SA Regional Water Quality and Water Quality Monitoring

The tools and methods that have been employed in South Africa assessed a wide array of water quality parameters, both quantitative and qualitative. These include pH, turbidity, dissolved oxygen, and chemical contaminants such as heavy metals, which are key indicators of pollutants, pathogens, and chemicals that pose a potential risk to both human health and ecosystem integrity [15]. However, only a handful of these test parameters are commonly investigated, as will be the case for this investigation [4]. These metrics must be selected while considering the contaminants that may be present in the local ecosystem [4]. According to Boyd and Alley [4], drinking water should not have excessive mineral concentrations, and must not contain any toxins and pathogens. The water quality metrics that will be

monitored in this investigation to ensure safe drinking water are total hardness, total chlorine, free chlorine, bromine, total alkalinity, and pH.

The list of chemical parameters mentioned above constitutes the components of the Water Quality Index (WQI) that will be used to evaluate water quality in this project [16]. The WQI is used in South Africa to condense multiple parameters into a unified value, simplifying the interpretation of water quality data [17]. The first WQI, known as the Horton Index, appeared in 1960 and is a simple and concise tool that allows the analysis and quantitative reporting of the quality of water [17, 18]. Moreover, the SANS guidelines provide thresholds and limits for these parameters, for various contaminants as well as the nuances that need to be considered when evaluating a complex water source, with more than one tributary and socio-medical purpose [18]. This is what determines the weight of each parameter in the WQI calculation. This comprehensive approach ensures a thorough understanding of water quality across various dimensions, setting the stage for evaluating the country's water quality trends over the past two decades.

3.1 South African Water Quality: 20 Years in Review

South Africa is recognised for its progressive water legislation, ensuring both the quality of water and meeting basic public needs through the implementation of human and environmental rights [19]. Despite this, the condition of the country’s water sources has been steadily declining, as noted in reports such as the Council for Scientific and Industrial Research (CSIR) 2010 and DWA 2011a [19]. Human activities have significantly impacted South Africa's water resources, leading to increased nutrient loads and toxic cyanobacterial blooms [20]. A decision in the late 1970s set a high effluent phosphate standard for water treatment works in "sensitive catchments" which exacerbated the eutrophication problem [20]. The deterioration of water quality in rivers and reservoirs since has been found to be due to increased effluent loads and challenges in ensuring compliance with water quality standards at sewage treatment plants [20]. A snapshot of the historic and current trends of environmental water quality in the country can give insight into the journey South Africa has been on for the last two decades in addressing its declining water quality.

In the early 2000s, South Africa's freshwater resources already showed signs of increased stress due to population growth and economic expansion [20]. By 2005, almost all freshwater resources in the country had been fully allocated, with declining water quality attributed to pollution from various sources [20]. The population growth rates and socio-economic trends of 2008 demonstrated that it would be unlikely that South Africa's water resources can sustain current usage patterns and pollution levels for decades to come. Projections suggested that by 2030, South Africa's freshwater resources may be fully depleted and unable to meet demand [20]. Even with a slow and steady growth in population size, pollutants will continue to accumulate in freshwater systems, necessitating improved management and treatment technologies to mitigate eutrophication and to address negative externalities and associated costs [20]. Urgent action, including a review of effluent quality standards and adequate education for the public, is required to address the risks [20]. Table 2.1 presents the actual water requirements for 1996 alongside the projected water needs for 2030, quantifying the country's water usage trends and estimated future demands [20, 21]. The table indicates that urban and domestic water supply demand will triple by 2023 – a demand that the current water supply will not be able to meet.

Table 2.1 Water requirements for 1996 and projected water requirements for 2030 across different sectors in South Africa (adapted from Basson *et al*.) [20, 21]

Sector	1996		2023		Volume Increase (%)
	Volume $10^6 m^3$/year	Sector Usage (%)	Volume $10^6 m^3$/year	Sector Usage (%)	
Urban and domestic	2 171	10	6 936	23	220
Mining and industrial	1 598	8	3 380	11	112
Irrigation and afforestation	12 344	62	15 874	52	29
Environmental	3 932	20	4 225	14	8
TOTAL	**20 456**	**100**	**30 415**	**100**	**52**

3.2 Assessing Water Quality Across South Africa's Provinces

The above projections are supported by the findings in recent water and pollution studies conducted across provinces that face challenges in water security in the country due to high populations and inadequate infrastructure, including vulnerable groups in rural and marginalised areas with limited access to financial resources [21]. In 2012, an experimental study in rural areas of Limpopo [22] highlighted significant water quality challenges faced by vulnerable communities with limited access to treated municipal water supply. These communities often rely on untreated water sources, including rivers, boreholes, springs, and rainwater harvesting, exposing them to ailments such as acute diarrhoea and dental fluorosis due to high levels of faecal coliforms and fluorides. Despite existing frameworks for water quality management, the study revealed a lack of technical capacity and adequate finances at the municipality level, leading to inefficient implementation of pollution control strategies [22].

Then, in 2021, a different study focused on the Mutangwi River in the Limpopo province, examined physicochemical parameters, trace metals, and microbiological indicators [23]. The study revealed poor overall water quality, with elevated Cd and Pb levels indicating a potential carcinogenic risk due to inadequate water treatment [23]. This ongoing trend of poor water quality was also reflected in a 2022 study that assessed drinking water quality in the Thulamela municipality [24]. While the second study found no significant carcinogenic health risks, it highlighted that the water quality was not suitable for human consumption, emphasising the need for consistently treated municipal water and community education on hygienic practices [24].

Finally, a 2022 study in rural communities of the Vhembe District focused on the challenges hindering the implementation of water and sanitation safety plans (WSSP) [25]. This study connected socio-economic factors such as poverty and unemployment to limited access to purified water and inadequate sanitation facilities, resulting in the spread of waterborne diseases within communities. Barriers like financial inequality, deteriorating infrastructure, and lack of natural water source protection were identified, stressing the importance of community collaboration and education to improve sanitation, to encourage safe practices and bring to attention the pitfall of perceptions [25]. These studies collectively illustrate the persistent and multi-layered issues contributing to poor water quality and sanitation challenges in the Limpopo province.

Similarly, a 2023 study on water security in rural Eastern Cape [26] identified the challenges related to the safety of drinking water found in the region. Despite national standards for water quality, the study shows that the standards of water in this region remain a safety concern. The research, based on interactions with 140 respondents, revealed that rural residents rely predominantly on dams, rivers, and streams for domestic and agricultural water needs. However, the availability of water throughout the

year is precarious due to changing climatic conditions, leading to competition for water resources between humans and livestock. This scenario highlights the vulnerability of rural communities to water insecurity, exacerbated by climate change impacts and poor infrastructure in Limpopo. Similarly, this emphasises the growing need for improved water management practices, infrastructure development, and climate-resilient strategies to ensure safe and sustainable drinking water access in rural areas of South Africa [26].

The severe cholera outbreak in Hammanskraal, north of Pretoria, resulted in 17 deaths, including two children, and 165 patients receiving treatment at Jubilee District Hospital by May 2023 [27]. This crisis is linked to long-standing issues with contaminated water, particularly due to the under-resourced and neglected Rooiwal wastewater treatment plant. For nearly two decades, residents have been exposed to unsafe water, contributing to significant health concerns [27]. This issue aligns with broader systemic challenges in the country, where many areas face inadequate infrastructure that may lead to similar outbreaks if not addressed through comprehensive water management and infrastructure improvements.

Corroborating this, a study of the lower uMfolozi floodplain system of KwaZulu-Natal, conducted in 2021 [28], also revealed the ongoing challenges in ensuring water quality and safe drinking water by focusing on the effects of land use on surface water quality. The study reported that while most water quality parameters met standards outlined for irrigation by the South African agricultural-water-quality (SAWQ) guidelines, there were notable exceptions such as elevated levels of electrical conductivity (EC), pH, nitrate content, the sodium adsorption ratio (SAR), chloride, and sodium concentrations in cultivated areas. These findings suggest potential risks to drinking water safety, especially considering that contaminants from agricultural activities can impact water sources. This study stresses the need for systematic monitoring to identify and address the role surface land use plays in the availability and protection required for drinking water sources. This can be in the form of supervised management practices and water treatment measures being deployed in the region [28].

These studies provide empirical insights into region-specific challenges that directly impact the availability and safety of drinking water. The findings of the studies conducted in Limpopo documents the ongoing challenges with poor water quality in rural areas, necessitating improved treatment and infrastructure, along with community education and proactive measures to address water pollution and safeguard vital water resources. The study in the Eastern Cape highlights the compounding factors of climate change, limited water availability, and reliance on potentially contaminated sources such as dams and streams. On the other hand, the research in KwaZulu-Natal focuses on the impact of agricultural practices on water quality, highlighting concerns about chemical contaminants in water sources. By identifying vulnerabilities in water sources and community reliance on natural water bodies, these studies underscore the point of the urgent need for integrated water management approaches to safeguard public health [23-28].

3.3 Challenges Faced by Vulnerable Communities: Rural and Peri-urban Regions in South Africa

In addition to the concerns discussed above, these provinces in South Africa share common challenges in water security and quality due to factors including drought, pollution, and inadequate infrastructure [29]. The geospatial aspects of economic water scarcity that stem from historical trends exacerbate this and can provide context for the results found in the studies above. South Africa's historical apartheid spatial planning has led to rural areas lacking basic water and sanitation services, despite efforts to address historical inequalities and socio-economic gaps since 1994 [29]. However, significant disparities persist in water infrastructure delivery between rural and urban areas, with rural provinces and small towns facing high infrastructure backlogs and unreliable water services. For instance, municipalities in the Eastern Cape and KwaZulu-Natal, particularly rural areas along the eastern

seaboard, and to a lesser extent in Limpopo, have notable infrastructure backlogs [29]. This gap persisted into 2019, disproportionately affecting rural households and marginalised groups, particularly poor African residents in the Eastern Cape, KwaZulu-Natal, and Limpopo. These challenges highlight ongoing investment disparities and gross inequalities in access to safe water and sanitation services, as shown by sources such as Masindi and Duncker [30] and the Parliamentary Monitoring Group [29].

South Africans consume approximately 237 litres of water per person per day, significantly surpassing the global average of 173 litres per day [29]. However, provinces such as Gauteng and the Western Cape with high population densities face severe physical water scarcity, which often coincides with limited freshwater availability, according to the FAO in 2007 [29]. Gauteng, in particular, was projected to experience significant net immigration, with estimates indicating a migration influx of 1.02 million people between 2016 and 2021 according to Stats SA [29]. This province attracts both international and domestic migrants, notably from rural areas in Limpopo, KwaZulu-Natal, and Eastern Cape. Similarly, the Western Cape serves as a significant immigration hub, experiencing substantial population growth in cities like Cape Town, which grew by 79% between 1995 and 2018. However, this growth hasn't been accompanied by a proportional increase in dam storage capacity, leading to heightened water demand at the residential level. This localised population surge and increased water consumption contribute to significant imbalances between water supply and demand.

The trend of high demand and poor water management observed across SA provinces indicates the multitude of water management challenges confronting these regions. Despite these regional differences, common themes emerge regarding the urgent need for integrated water management approaches, improved treatment infrastructure, and community education to address water pollution and ensure safe drinking water in rural and peri-urban areas.

A study conducted by Verlicchi and Grillini in 2020 discusses the challenges of ensuring safe drinking water in rural areas of Sub-Saharan Africa due to various natural and human-induced pollutants [31]. The study asses the water quality of surface water and groundwater quality in rural and peri-urban areas in South Africa, focusing on conventional pollutants, inorganic chemicals, microorganisms, and micropollutants. It also highlights the lack of data and challenges faced in decentralised water treatment. High concentrations of microorganisms and nickel were observed in surface water, while arsenic and lead were detected in groundwater. Micropollutants such as ibuprofen, acetylsalicylic acid, clozapine, and estriol showed significantly higher concentrations in surface water compared to the developed world, in particular, European rivers [31]. The study makes clear the need for consistent monitoring of water sources to provide suitable treatment to ensure safe drinking water, alongside improving wastewater treatment in rural areas to protect water sources [31]. The danger posed by the lack of knowledge locals in these areas have about these water sources is presented in the study’s conclusion, which states that the impact of untreated or inadequately treated effluents on surface water quality not being fully known demonstrates the need for continuous monitoring and management of water treatment plants [31].

In SA, the treatment of rural settlement wastewaters is barely existent [32]. This results in a decline in the quality of nearby surface water as well as the local groundwater reserves due to percolation or infiltration [33]. This further proves that despite efforts to address water quality challenges, South Africa has not made significant progress from the previous concerns highlighted in the timeline, for both surface water and groundwater quality. The European project H2020 SafeWaterAfrica is mentioned as contributing to filling knowledge gaps in water treatment for small communities in SA [34]. Understanding South Africa's water quality challenges from empirical data is crucial, yet juxtaposing these findings with public perception provides a deeper understanding of why these challenges have gone unchecked for so long.

3.4 Public Perception of the Safety of Drinking Water in South Africa

A study conducted by Wright et al. on perceived drinking water safety in South Africa analysed trends using data from general household surveys spanning 2002 to 2009 [35]. This investigation relied on information from over 50,000 households and considered public perceptions alongside factors such as disease outbreaks, water supply improvements, and household characteristics. The increase in the public perception that their drinking water was safe during this period can be attributed to improved supply coverage due to advancements in water supply infrastructure and enhancements in water taste, odour, and clarity. This stability in perceived safety is noteworthy, especially considering a significant cholera outbreak experienced between 2000 and 2002 [35]. The study found that factors such as water taste, odour, and clarity were more influential in shaping perceived safety than socio-economic or demographic factors. This aligns with studies from developed countries that often emphasise areas that had access to bottled water, private supplies, and trust in municipal water. Conversely, in developing countries like South Africa, perception studies tend to focus on home water treatment and source choices. The study also highlighted the role of information dissemination, noting that it can influence public perceptions and behaviours regarding water safety. Initiatives like South Africa's Blue Drop scheme and Rand Water's outreach programs played a visible a role in informing and engaging the public about water quality issues [35].

By 2011, concerns had arisen, especially in rural areas and small towns, as reflected in the Blue Drop Report published during that year [36]. The study surveyed urban South Africans and found that 81% perceived their tap water as safe [36]. The organoleptic properties and sensory aspects such as appearance, taste, and odour, along with cleanliness were still considered to be a major indicator of good water quality and municipal service [36]. However, the study also revealed areas where public understanding is lacking, such as awareness of Blue Drop status, the impact of chlorine on water safety, and understanding of water treatment processes. These communities were unaware of the decline in the quality of their water. It recommends introducing educational campaigns and leveraging social networks for effective communication on water safety to all citizens [36].

The discrepancy between public perceptions of drinking water safety from 2002 to 2009 and the actual water quality challenges faced by South Africa is stark. Despite the stable public perception of drinking water safety shown in the study, South Africa's freshwater resources have been under increasing stress since the early 2000s. Recognising the difference between public perception and actual water quality can influence policy decisions, education, environmental protection, and collaboration between citizens and organs of state. It also emphasises the need for education and awareness, and how this can put pressure on the country's water authorities to foster trust and transparency in water management.

3.5 The Current State of South Africa’s Water

Between 2000 and 2011, urban South Africans generally perceived tap water to be safe. However, by 2023 – over a decade later – citizens had become increasingly aware of the deteriorating water quality across the country, including in rural areas and small towns [37]. The latest Blue Drop Report, released by the Department of Water and Sanitation (DWS), presents a concerning decline in the quality of drinking water since 2014 [38]. The report found that 46% of water systems exhibited poor or bad microbiological water quality, marking a significant deterioration compared to previous years. Covering 958 water supply systems across 144 water services authorities, the report assessed infrastructure, maintenance, treatment processes, and staff expertise [38].

The findings highlight a growing number of systems in critical states of performance. While metropolitan areas such as Gauteng and the Western Cape showed better-performing systems, regions such as the Northern Cape faced a majority of systems in poor or critical condition [38]. The accompanying No Drop Report, which evaluates non-revenue water (NRW) and water losses, revealed

a national increase in NRW from 37% in 2014 to 47% in 2023 – well above the international average. Contributing factors included leaks, inadequate metering, illegal connections, and billing inefficiencies. The report urged municipalities to enhance infrastructure management, improve metering and billing, and engage in community education to address water losses [38]. The Green Drop Progress Assessment, which focuses on wastewater treatment plants, reported that 64% of plants were at high or critical risk of releasing untreated or partially treated water. This poses significant environmental and public health risks. Collectively, these reports indicate a concerning decline in drinking water quality, escalating NRW levels, and deteriorating wastewater treatment systems since 2014 [38]. They highlight the need for collaborative action to address these challenges.

The pollution of municipal water sources further illustrates these issues. A May 2023 report by the DWS revealed that pollution in the Leeukraal Dam, which supplies the Temba Water Treatment Works serving the City of Tshwane, was so severe that the Temba facility could not treat the water to meet South African National Standards for safe drinking water. As a result, Tshwane residents had to rely on water tankers for domestic use [39]. This ongoing pollution, largely caused by untreated sewage, was first highlighted in the 2022 Green Drop Report and remains evident in the 2023 Green Drop Watch Report [40]. These reports reflect the government's inability to respond promptly to water quality crises.

In June 2023, Eyewitness News reported that the DWS had recorded a significant decline in water quality. The testing of 151 water sources revealed that 50% of samples failed to meet acceptable microbiological standards [41]. The DWS Director-General, Dr Sean Philips, warned that some municipal water systems had produced drinking water during the 2021/22 financial year that fell short of the SANS 241 standard, posing potential health risks [41]. A subsequent report by the same outlet noted concerns about the 2023 cholera outbreak, with the Minister of Water and Sanitation, Senzo Mchunu, cautioning that poor water quality could sustain future outbreaks of waterborne diseases [42]. The dire state of water quality, coupled with the spread of waterborne diseases, underscores the urgent need for rapid, reliable, and accurate solutions to monitor and improve water quality across SA.

4 Real-world Applications and Their Limits

A common thread seen through the studies mentioned above is the inability of traditional methods for water monitoring and quality assessment to completely and accurately capture both the challenges of poor water quality and its impact on the local population and aquatic systems. Conventional tools and methods for water quality assessment have relied on manual testing kits, laboratory analysis, and field measurements, which are still relevant but have inherent limitations [43]. These methods involve collecting an assortment of water samples, conducting chemical tests, and analysing the results to determine water quality parameters. While these approaches can provide accurate data, they are often resource-intensive procedures that are time-consuming, require specialised equipment and expertise, and can be costly, especially for widespread monitoring programs. The WHO's manual on water quality monitoring outlines these traditional methods and their applications in assessing microbial and chemical water characteristics and contaminants [44]. Similarly, several of the water management programs in SA rely on outdated technology and time and resource-consuming techniques that do not yield adequate results [45]. The water quality decline discussed above is occurring despite the water management structures, strategies, programs, instruments, and tools put into action to manage and report on water quality across the country [46]. Evaluating these systems provides some insight into the strides that have been made in the field and the limited improvements on the country's water.

4.1 Practical Initiatives Currently Implemented in South Africa

To address the decline in water quality, organisations such as the Water Research Commission have created and implemented various monitoring programs in South Africa, both longstanding and recent

[47]. These programmes aim to improve water security and to capture monitoring data for decision-making, although often lacking follow-up after reserve studies. Table 2.2 summarises these initiatives.

Table 2.2 Water monitoring initiatives implemented in collaboration with the WRC [47 – 50]

YEAR ESTABLISHED	PROJECT TITLE	DESCRIPTION
1970s	National Chemical Monitoring Programme (NCMP)	▪ Well-established programme monitoring surface and groundwater. ▪ Good data available for pH, salinity, major ions, and nutrients but limited for metals, organics, etc. ▪ Groundwater data is less standardized; better cooperation with other organizations needed.
2002	National Eutrophication Monitoring Programme (NEMP)	▪ Monitors eutrophication in reservoirs across SA. ▪ Collects data on chlorophyll levels and provides guidelines for management.
2004	National Microbial Monitoring Programme (NMMP)	▪ Monitors faecal contamination in surface water to assess health risks and effectiveness of protection measures. ▪ Attempts to merge local authorities' data with DWA's system for comprehensive monitoring.
2008-2009	National Toxicant Monitoring Programme	▪ Aims to assess trends in toxicants of surface and groundwater. ▪ Response to increasing concern about toxicants in water resources.
2016	The River Eco-status Monitoring Programme (REMP)	▪ Focuses on ecological health of water resources, primarily through the River Health Programme (RHP). REMP evolved from the RHP established in 1994. ▪ Produces State of the River reports but lacks coverage of estuaries and wetlands. ▪ REMP replaced the RHP and is a component of the National Aquatic Ecosystem Health Monitoring Programme (NAEHMP).

Limitations in SA water quality monitoring programs, as identified by studies such as those conducted by the WRC [47] and Rivett et al. [51], include sparse data availability for tested parameters like metals, toxic chemicals, and organic pollutants, along with inconsistencies in data standardisation, resource constraints impacting monitoring frequency and coverage, and a lack of real-time monitoring capabilities, particularly in low-resource areas.

Peletz et al. [52] attempt to answer the question of why water quality monitoring programs succeed or fail in their comparative analysis study of regulated testing systems across sub-Saharan Africa. The authors concluded that institutional commitment, comprising motivation and leadership, knowledge, and staff retention, plays a role in determining monitoring performance, especially in weak regulatory environments. They argue that while supply-side interventions such as infrastructure and training are indispensable, complementary strategies for motivating and incentivising water supply and surveillance agency managers are equally necessary for achieving testing goals and ensuring long-term sustainability [52]. This is also echoed in the WRC report [52], indicating that beyond data and resources, all stakeholders need to play an active role in the implementation and ongoing maintenance of the program, thereby encouraging the enlistment of citizen science.

In line with this, Crocker and Bartram's study [53] fills a gap by examining monitoring needs and methods, evaluating incremental expenses, and pinpointing economic limitations in South Africa, and six other countries representing various water supply scenarios. The demands for monitoring drinking

water quality differ depending on the socio-economic situation facing the country. Surveillance monitoring typically necessitates the highest number of tests per year per person (12.09 tests/year/1000 capita), followed by operational monitoring for small water supplies (8.28 tests/year/1000 capita), and then operational monitoring for large supplies (2.53 tests/year/1000 capita served). This elevated need for testing is due to operational monitoring potentially having higher testing frequencies, non-piped water sources are not typically operationally monitored but are instead covered under surveillance in eight out of nine study locations, with South Africa being the exception. At the time the study was conducted, South Africa had 43% of its population living in a rural setting. The research suggests potential optimisations in monitoring programs by considering field-based testing and re-evaluating approaches for non-piped water supplies, aiming to improve the effectiveness and efficiency of water quality management in these settings by not only addressing the need to monitor piped water but to monitor large water reservoirs to limit the need for frequent testing of residential drinking water [53].

4.2 New Technologies Bridging the Gap

The advent of innovative technologies including machine learning techniques presents promising solutions to overcome the constraints of traditional water quality assessment methods, as discussed as part of the monitoring initiatives [43]. This includes automating data collection, enhancing data accuracy, and providing cost-effective options for comprehensive water quality management strategies in South Africa [54]. Integrating computer vision algorithms with visual data analysis techniques enables real-time monitoring of water quality parameters, facilitating rapid and continuous data collection [55]. Tian et al. [55] point out the challenges in conventional water quality monitoring and highlight the potential of innovative technologies such as computer vision to address these issues. Computer vision-based systems can automate the analysis of water test strips, accurately detect changes in visual data, and measure physical and chemical parameters [56]. These advanced technologies not only enhance the effectiveness of water quality assessments but also enable timely interventions and decision-making [57].

To tackle the above-mentioned shortcoming in conventional monitoring efforts, there has been a revolution in water monitoring around the globe. Conventional approaches used to assess water quality include electronic instruments and chemical substances used in laboratory settings which are time-consuming with significant delays before any results can be obtained [58]. The most commonly used are physical, chemical, and biological methods [58]. The technologies based on these methods include the Arduino-based water quality monitoring system [59, 60, 61], remote sensing technology [62], mobile applications for water quality monitoring [63], smart water metering systems [64] and more recently Internet of Things (IoT) monitoring [65-67]. There is also a strong drive to shift from conventional methods to more advanced methods such as UV absorption technology to address the shortcomings of traditional chemical methods [68]. However, the most prominent technologies under development use colourimetric techniques [69] and electro-chemical sensors [70, 71] to assess freshwater reserves. Mobile technology that uses machine learning techniques [72] along with portable water testing kits for water quality monitoring is gaining traction [73-75]. The key advantage of ML-based real-time monitoring systems is their ability to automate continuous sampling and monitoring with portable devices instead of expensive professional equipment [76].

4.2.1 Mobile Applications and AI

South Africa has developed two smartphone applications to address water management. The Water Wise application, developed by the DWS, provides users with information on water-saving tips and helps users locate water service providers [77]. Another application is the eThekwini Water and Sanitation application, which helps users pay their water bills and report water faults [77]. However, none of these applications provide real-time water quality assessment information. The National Water

Quantity Monitoring System provides data on water levels of water reserves [77, 78]. The national Blue Drop System is ineffective in water quality monitoring in rural municipalities [51]. Smart applications such as FlowTracker [79, 80] and DropDrop [81] allow users to monitor flow rates and measure water usage, respectively, but they do not track water quality. Smartphone applications using AI techniques have been developed in other countries to monitor water quality. For example, the Water Watcher application, a collaboration between IBM Research Africa and the Kenya Marine and Fisheries Research Institute, analyses water clarity, colour, and turbidity using smartphone cameras and machine learning algorithms [82]. Similar applications have been launched in other countries such as China and the USA to analyse water samples and classify the level of contaminants in the water [83]. In South Africa, there are currently no similar applications for water quality monitoring that have been implemented nationwide [84, 85].

5 Machine Learning and Computer Vision in Water Quality Assessment

Machine learning and computer vision, key enablers of modern technologies, have evolved significantly and play a role in smartphone-based water quality monitoring through diverse methods and applications.

5.1 Development of Machine Learning

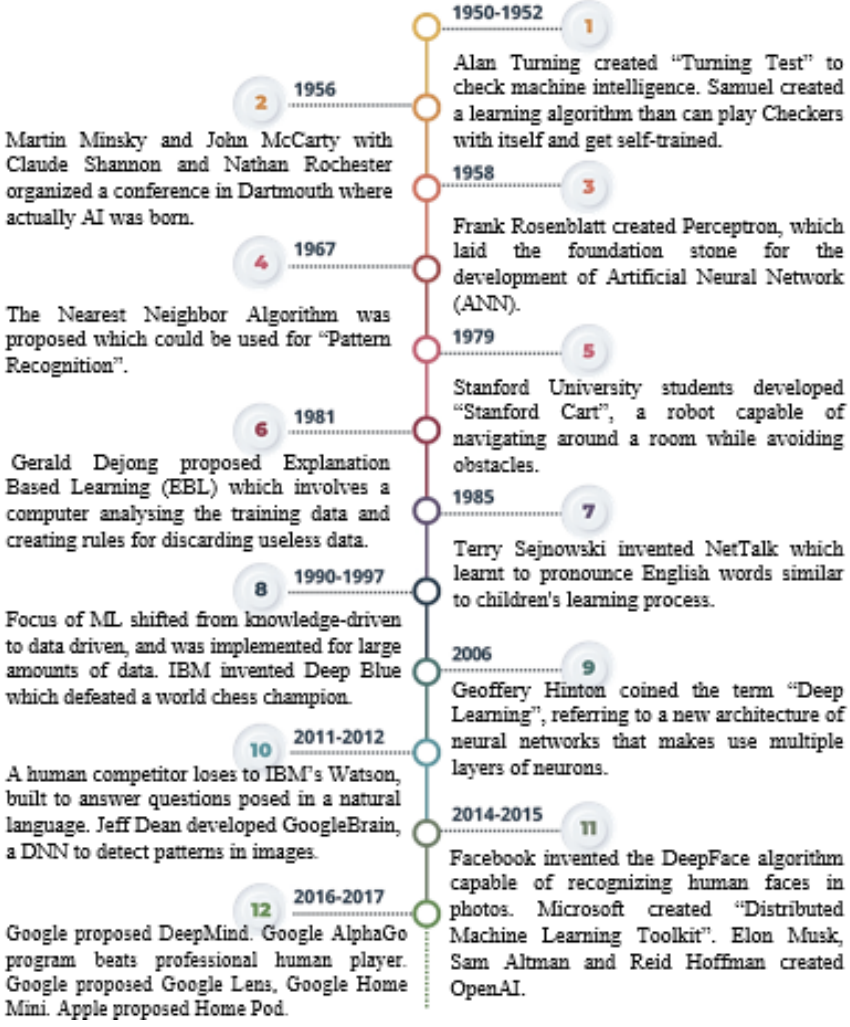


Fig. 2.1 Timeline of key ML developments [90]

Having discussed the technological advances in water quality monitoring, the role of AI, more specifically machine learning and computer vision, can be clarified by reviewing a summary of the history, approaches, and applications of ML. The phrases 'machine learning' and 'artificial intelligence' were originally introduced in 1952 and 1956, respectively [86]. Machine learning is generally used to describe automatised, highly flexible approaches within high-performance computational requirements to identify patterns in complex data structures [86]. Arthur Samuel [87], a renowned figure in the field, described machine learning as the ability to provide computers with the capability to learn without explicit programming. One of the key landmarks of ML occurred in 1986 when Geoffrey Hinton [88] co-authored Learning

Representations by Backpropagating Errors. Hinton, a cognitive psychologist and a computer scientist is known as the father of machine learning. His contributions to the field of deep learning, generative models, and convolutional neural networks (CNN) made him a pioneer in the discipline [88]. Embedded ML or TinyML is a growing trend as of 2020 [89], which integrates AI algorithms directly into systems and devices. This demonstrates that ML is expected to shift focus to smart devices and the use of ML in everyday tasks, such as smartphone applications. Figure 2.1 shows a timeline of the history of machine learning since its first significant implementations, setting the scene for smartphone applications such as the one discussed in this investigation.

5.2 Machine Learning Paradigms

The various types of machine learning paradigms can be characterised into four main categories for the purposes of this investigation, depending on the data requirements during and after training, the training process followed and the final output [90]. These categories include supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning [90] as shown in Figure 2.2.

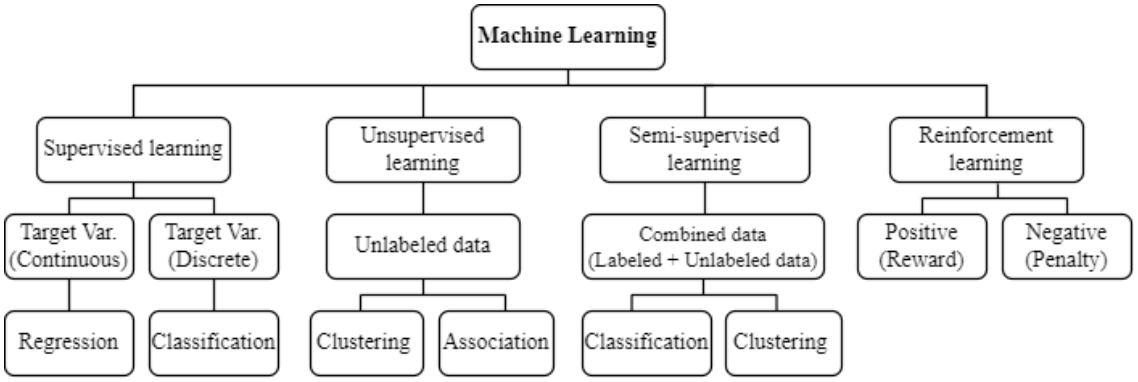


Fig.2. 2 Types of machine learning techniques [90]

5.3 Supervised Learning: Data Collection and Uses

Supervised learning will be used to develop the smartphone application in this investigation. It is an ML strategy that seeks to study the system's input-output relationship using a set of paired input-output training examples in the form of training data. Supervised learning leverages training data to identify patterns and boost performance in numerous tasks such as prediction [89]. In this paradigm, the output is considered as the label or guided supervision for the input data, while the training samples are described as labelled or supervised data [90]. The primary benefit of employing supervised learning is that once the algorithm has gained a sufficient understanding of the underlying patterns in the data, it can autonomously carry out its tasks and perform analysis and provide meaningful outputs that can easily be interpreted by humans [92]. However, one major challenge is the cost and difficulty of collecting large volumes of high-quality labelled data. This hurdle can limit the applicability of supervised learning.

5.4 Approaches to Supervised Machine Learning

There are a number of approaches to supervised machine learning, which make use of a labelled dataset to train a model to make predictions or classify new, unseen data. This includes but is not limited to decision trees, random forests, support vector machines (SVM), Naïve Bayes, K-nearest neighbours

(KNN), and neural networks [93]. Neural networks are of particular interest as that is the ML algorithm type that will be used to build the classification model. Artificial neural networks can be used to solve complex problems. ANNs mimic the structure of the brain, using interconnected artificial neurons to analyse information and to classify new data. The strength of these networks lies in the ability to leverage the connections between neurons which hold numerical values as a way to store information [94]. Recurrent neural networks (RNNs) are capable of solving problems related to natural language processing (NLP) [94]. Convolutional neural networks are typically used to classify images as it possesses the ability to acquire hierarchical features such as textures, shapes and boundaries. This allows them to accurately recognise distinct objects in images. The aim of training a CNN is to learn which features to extract from the provided training set, automatically. CNNs are most effective at solving machine vision-related problems [94]. The CNN organizes the above-mentioned neurons into layers [94]. This includes input layers, numerous hidden layers and an output layer. The more layers are deployed in the model, the more processing can be done to find complex patterns [94]. Therefore, the use of a CNN is the most appropriate neural network to use in this case, as machine vision, also known as computer vision, will be one of the techniques used to perform the classification task [94].

5.5 Computer Vision and Its Applications in Environmental Analysis

Computer vision, which often uses image processing, is a branch of computer science that focuses on enabling computers to interpret and understand visual information from the environment [95]. Digital image processing refers to the study of theories, models, and algorithms used for the manipulation of images, primarily through computer-related technology. While computer vision focuses on theories and algorithms aimed at automating visual perception processes. This includes tasks such as noise removal, edge smoothing, edge sharpening (low-level vision), segmentation of images to isolate object regions, description of segmented regions (intermediate-level vision), and interpretation of scenes (high-level vision). The concepts of image processing and computer vision share significant overlap, with both fields contributing to advancements in automated visual processing [95].

In the context of environmental analysis, computer vision algorithms can process images or videos captured from sources such as water bodies to extract valuable insights within the field of AI. This may include detecting water quality characteristics, identifying pollutants or contaminants, and monitoring changes in aquatic ecosystems over time [96]. By leveraging computer vision, researchers can automate the analysis of large volumes of visual data, which would be impractical to process manually [96].

5.6 The Development of Computer Vision

Larry Roberts is widely recognized as the pioneer of computer vision, particularly for his work in extracting three-dimensional geometrical information from two-dimensional perspective views of blocks, outlined in his Massachusetts Institute of Technology Ph.D. thesis in the 1960s [97]. Following this, many researchers in AI, both at MIT and elsewhere, began to investigate computer vision within the context of the "blocks world" [97]. The focus initially shifted towards addressing real-world images, leading to extensive research in low-level vision tasks including edge detection and segmentation. A significant development in this realm was David Marr's framework proposed in 1978, which adopted a bottom-up approach to scene understanding [98]. Despite Marr's paradigm being influential, recent years have seen some researchers advocating for a more top-down and diverse approach, known as Purposive Vision, credited to Yiannis Aloimonos from the University of Maryland [99]. Over time, computer vision has merged with related fields such as photogrammetry and computer graphics. Figure 2.3 graphically represents a history of computer vision milestones to date.

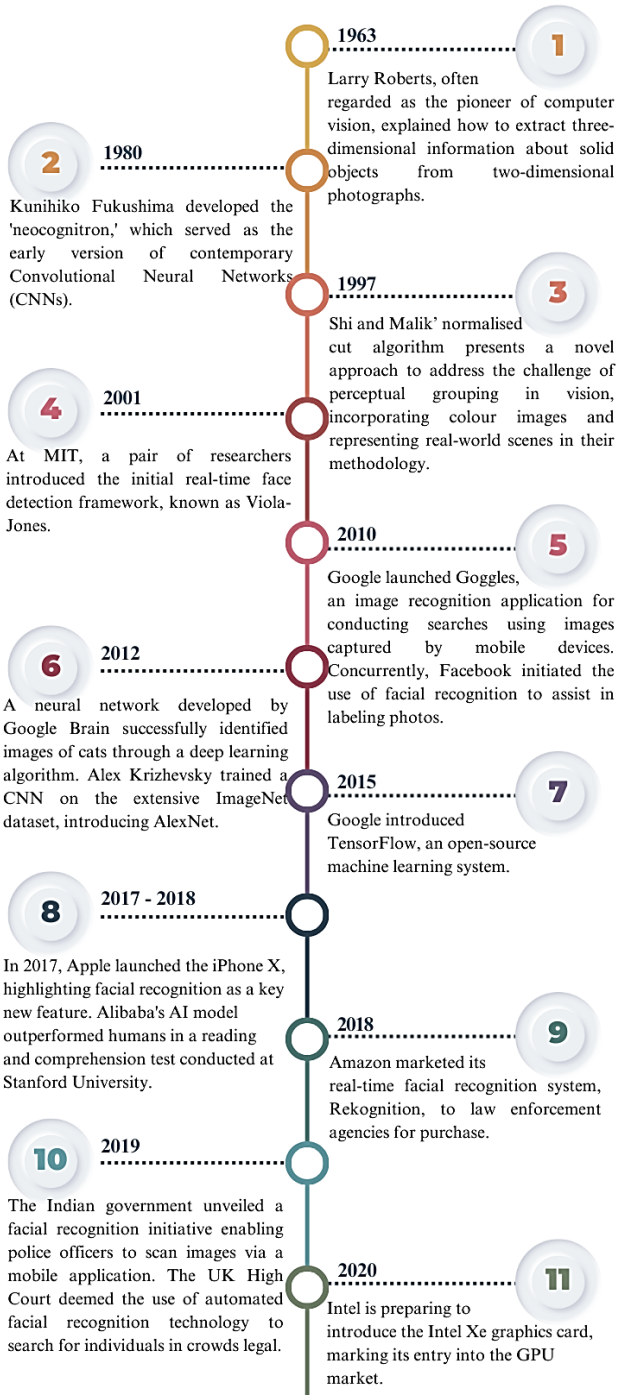


Fig. 2.3 Timeline of milestones in computer vision [100, 101]

5.7 Machine Learning in Computer Vision Used for Monitoring Systems

The symbiotic relationship between computer vision and deep learning has led to significant advancements in both domains over the past decade. Real-world applications of CV, such as self-driving cars, face detection, security systems, and medical diagnostics including cancer detection, showcase the practical impact of these technologies [102]. The role machine learning plays in enhancing computer vision capabilities has grown rapidly with the development of advanced monitoring techniques, especially in environmental monitoring system applications [103]. One significant way these two concepts interact is through the development of sophisticated algorithms used to analyse large volumes

of visual data to extract defining features about the environment, including physical characteristics, trends over time, and environmental anomaly detection [104]. One such application is the use of satellite imagery analysis for environmental monitoring [105]. Machine learning algorithms can be trained to identify and classify different land cover types, such as forests, urban areas, and agricultural fields. This classification process enables the detection of deforestation, changes in vegetation cover, or illegal land use practices [106]. Furthermore, machine learning algorithms can learn to detect specific environmental indicators and trends such as pollution hotspots [103] or wildfires [107] by analysing patterns and anomalies in satellite imagery, as well as predict environmental trends, such as terrestrial carbon balance estimations [106] and forecasting air quality levels based on historical data and meteorological factors [103].

Regarding water monitoring, machine learning algorithms are capable of analysing satellite images or drone footage of water bodies. These algorithms can identify and classify different water quality indicators, including algae blooms, sedimentation levels, and pollution sources including oil spills [108] and industrial discharges. Additionally, machine learning algorithms can predict water quality trends, enabling the implementation of proactive measures to maintain safe and sustainable water supplies. Through the use of machine learning, environmental authorities can automate the detection of water quality issues, track changes over time, and design targeted interventions [103].

5.8 Existing Computer Vision and Machine Learning Applications for Water Quality Assessment

5.8.1 Machine Learning Applications

As supervised learning can allow machines to learn human or object behaviour in specific tasks, machines that become proficient in performing these tasks can do so faster and more accurately than humans, as they can process input-output mappings quickly and continuously. However, owing to limitations in both hardware and software designs, current supervised learning algorithms fall short of superseding and often even matching human learning capabilities when tackling complex tasks. There are fields where these algorithms have been successfully applied though. This includes information retrieval, data mining, speech recognition, bioinformatics, and cheminformatics [92]. When looking at ML applications in Africa, fields such as medicine, agriculture, cyber security, and other industries have benefited significantly from machine learning [109]. Examples of the use of these ML algorithms include cyber security intrusion detection, disease detection, sleep stage classification, face mask detection during the COVID-19 pandemic, optimisation methods in optical communications, software, and electronic engineering, and advancing medical research through deploying AI in clinical settings [109]. NLP has also resulted in the use of ML for language translation and automation. This overview simply serves to highlight ML's wide and valuable contributions to several fields across the African continent [109]. A glaring lack of ML being used for water monitoring or smartphone applications is evident in the history of these applications, specifically in South Africa.

5.8.2 Computer Vision Applications

When assessing the potential of computer vision applications, two main criteria are worth considering: image content-based indexing and retrieval, and the development of vision-based human-computer interfaces [110]. These systems efficiently manage visual data and enable intuitive interactions with virtual environments, enhancing user experiences. Another promising application is creating virtual agents using parameters from real people's video sequences, which has implications for simulations, entertainment, and storytelling for interactive platforms that can be deployed in a mobile application format. These computer vision applications promise enhanced functionalities and immersive experiences across multiple domains [110].

The adoption of knowledge-based computer vision techniques has diversified extensively across various sectors. In autonomous driving systems, computer vision aids collision prevention and lane departure warnings via cameras [111]. Surveillance systems use deep learning for facial recognition and image analysis. Smart search technologies enhance object identification in images, while vein authentication and medical image analysis showcase computer vision's versatility in healthcare [111]. In entertainment, match move technology and projection mapping offer immersive visual experiences, and in medical contexts, gesture recognition systems enable touchless interactions during surgeries. Additionally, knowledge-based vision systems enhance object identification accuracy and efficiency through object-oriented models and relationship descriptions [111].

The gap in CV research and development in Africa is evident from the limited representation of African institutions in top-tier publications and the lack of consistent growth compared to other continents, indicating a need for more investigations and applications in this field to bridge these disparities and unlock the full potential of computer vision technologies across various sectors [112].

5.8.3 YOLO-based Object Detection Using Computer Vision

The specific supervised machine learning application that will be used for this investigation is object detection. Object detection is based on the identification and localisation of objects within images or videos. Several technologies have been developed to address this challenge, including region-based convolutional neural networks, single-shot detectors (SSD), and You Only Look Once (YOLO) algorithms [113]. Each of these technologies employs distinct methodologies for object detection, with YOLO standing out due to its processing efficiency and real-time processing capabilities [113]. The YOLO algorithm combines both machine learning and computer vision in performing its object detection tasks. This is a deep learning-based algorithm that uses CNNs to perform real-time object detection in images or video [114].

The YOLO algorithm, introduced in 2015 by Redmon et al., represents a significant advancement in object detection methodologies, especially for real-time applications [114]. YOLO differs from traditional approaches by adopting a single-stage detection model that processes the entire image at once and predicts bounding boxes and class probabilities directly, eliminating the need for multiple passes through the image. Additionally, its ability to handle small-size objects effectively further strengthens its suitability for tasks requiring precise object localisation and identification [114]. This approach results in faster inference times and improved efficiency. This speed is critical for applications where real-time monitoring and response are essential, for key tasks such as identifying pollutants, wildlife, or environmental anomalies using environmental monitoring tools and surveillance systems for effective interventions [113].

From YOLOv1 to YOLOv2, advancements included the introduction of anchor boxes for better localisation accuracy and an increase in model depth for improved performance. YOLOv3 introduced multiple scales for detection and a better backbone network, enhancing both speed and accuracy. YOLOv4 further refined the model with advanced techniques such as CSPDarknet53 and PANet, improving precision. In January 2023, Ultralytics [114] introduced the latest version of YOLO, known as YOLOv8, after releasing YOLOv5 in 2020. The initial assessments comparing it to its predecessors reveal its advancement as the new leading YOLO model. This version promises hardware-efficient architecture and superior real-time performance, marking a significant milestone in the continuous development of the YOLO object detection framework [114]. Figure 2.4 illustrates the superior performance of YOLOv8 compared to YOLOv5 and YOLOv6 when trained on 640 image resolutions. All versions of YOLOv8 exhibit improved throughput with a similar parameter count, indicating efficient hardware usage and architectural enhancements. The release of YOLOv5 and YOLOv8 by Ultralytics, with the latter showcasing impressive real-time performance, indicates that YOLOv8

prioritises fast inference speed for deployment on resource-constrained edge devices [114], making it ideal for the use of software deployed on mobile devices.

Current practical applications that use this technique range from object detection for traffic safety and

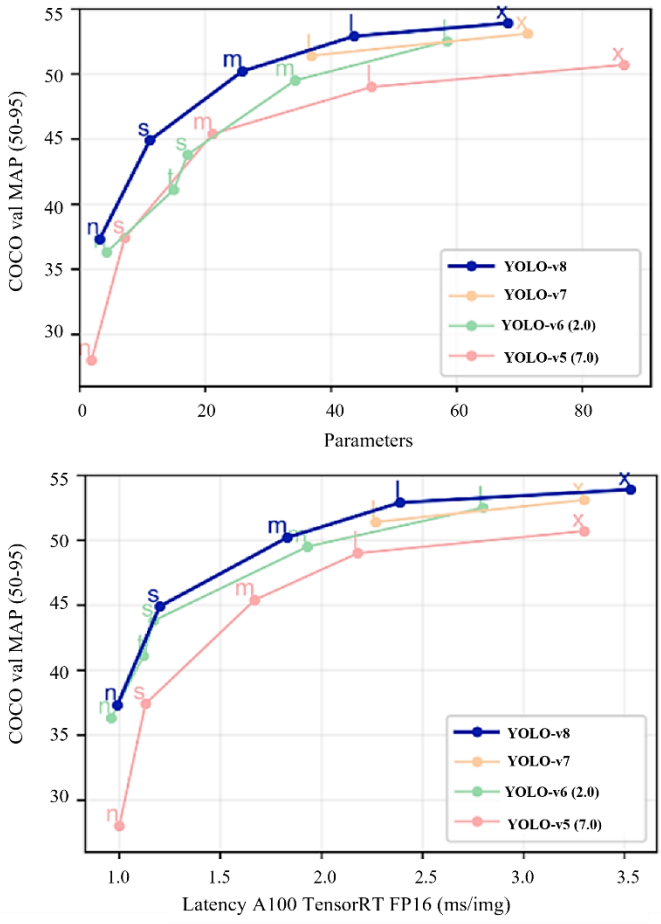


Fig. 2.4 Graph of YOLOv8 compared with predecessors [115]

emotion recognition to data analysis in intelligent environments. Notable software tools such as TensorFlow [116] and OpenPose [116] facilitate object detection. However, challenges include data annotation and labelling, addressed through deep learning and convolutional neural networks.

6 Colourimetric Analysis for Water Quality Testing

This section provides an overview of colourimetric analysis, industry standards for interpreting test strips, challenges in current methods, and the advantages of using modern technologies for water quality testing.

6.1 Overview of Colourimetric Analysis and its Principles

Water test strips, commonly used in colourimetric analysis, consist of reactive pads or zones impregnated with specific reagents. When immersed in water samples, these pads undergo chemical reactions that result in colour changes corresponding to different water quality parameters. Colourimetric analysis is a common form of using this to perform chemical analyses on these pads – a quantitative analytical technique used to determine the concentration of a substance in a solution based on its colour intensity. This method relies on the principle that the colour intensity of a solution is directly proportional to the concentration of the substance being analysed, indicating the presence and concentration of specific chemicals or contaminants [117].

In a traditional laboratory setting, this is done using a chemical assay and analysing the results with a spectrophotometer to analyse the colour change observed. It is one of the oldest water analysis methods [117]. This can be done using test strips, also referred to as colourimetric sensor strips, where the strip can be observed and recorded while it undergoes a chemical reaction that leads to a visible change in colour in response to specific contaminants in the water [117]. Historically, this used to be a very expensive and precise procedure that required bulky laboratory equipment and technical skills. In an attempt to address these challenges, user-friendly, portable, and inexpensive water test kits typically containing test strips, a colour card, and a manual have become commercially available [118]. Most commercial kits rely on the user's ability to manually determine the extent of the colour change and to then compare this observed change to the provided colour card to determine their water quality.

Recently, the use of smartphones to perform this analysis instead of normal readings, has gained traction, with smart devices can be transformed into ideal portable colourimetry tools as the use of image-based colourimetry is contactless, inexpensive, and potentially more accurate than manual readings [119]. However, this technology is still in its infancy.

6.2 Interpreting Colour Changes in Test Strips for Parameter Identification According to Industry Standards

Water test strips are observed to undergo a colour change upon interaction with water, these results are typically recorded in a formal setting and compared to existing measurements or quantitative data points. For instance, during the evaluation of a strip testing for chlorine, hardness, and other chemical parameters, the strip exhibits distinct colour changes indicative of their respective concentrations. The interpretation of these colour changes allows users to determine to what extent these chemicals are present and by extension the quality and safety of water [120].

In order to standardise the findings from such tests, the interpretation of colour changes in water test strips, as explained above, must align with industry standards such as the ISO 5667 series and ISO 7027, which provide guidelines and performance criteria for water quality assessment methods [121].

The International Organization for Standardization (ISO) is a key player in establishing industry standards for colourimetric analysis in water quality assessment [121]. ISO standards, such as the ISO 5667 series and ISO 7027, provide comprehensive guidelines and requirements for conducting colourimetric analysis of water samples. These standards outline the principles, methodologies, and performance criteria for colourimetric methods used to assess various water quality parameters.

More specifically, the ISO 5667 series of standards offers detailed guidance on water quality sampling, preservation, and laboratory analysis techniques. In particular, ISO 5667-3 focuses on the preservation and handling of water samples for chemical analysis, including colourimetric methods. The standard ensures that water analysis procedures are accurate and reliable for water quality data.

Moreover, by adhering to ISO standards, water quality laboratories and environmental monitoring agencies ensure that colourimetric analysis methods used in water quality assessment are consistent, accurate, and compliant with international guidelines. For commensurability and to establish international compliance, these standards and frameworks must also be adhered to by governing bodies, organisations and developers that create tools for widespread use in water quality analysis in order to meet international compliance [121].

6.3 Challenges and Limitations of Available Test Strip-Based Colourimetric Analysis

Some of the most commonly used rapid water test strips in South Africa include Macherey-Nagel rapid test strips [122], Hach test strips [123], Palintest pool water test strips [124], and LaMotte Insta-TEST® strips [125]. Each is designed for assessing a range of chemical water quality parameters. The iLab strips – which is the type of test strip used in this study – allow non-scientific field operatives to conduct basic water quality screening to address contamination issues. The kit works by conducting tests that identify sewage, industrial, or agricultural contamination, providing preliminary results on the presence of harmful chemicals and bacteria [126]. However, the manual analysis process used in these tests may not be comprehensive enough to capture all nuances of water contamination accurately. The main challenge with manually reading colour changes and comparing them to a colour chart is the potential for human error and subjectivity, leading to inaccuracies in interpreting water quality test results [127].

The Organisation Undoing Tax Abuse (OUTA) is a non-profit civil action organisation based in South Africa that aims to combat corruption, promote good governance, and encourage accountability in the public and private sectors. OUTA's WaterCAN initiative, more specifically their Water Testing and Training project, focused on promoting clean and safe water [128]. This aligns with iLab's goal of accessible water quality testing. Through WaterCAN's citizen science approach, activists use iLab's water testing kits to conduct testing across South Africa, contributing water quality data to their database – Map My Water – to ensure the safety and sustainability of water resources [128].

The current mobile applications that read these tests strips that are available on the market and their limitations must also be reviewed. A technical analysis of the current industry standard highlights the gaps and limitations of water quality monitoring using a smartphone application can also be explored by conducting chemical tests. At the forefront of the field is the JBL water monitoring application. The JBL company is currently one of the most prominent suppliers of aquarium, terrarium, and garden pond products in Europe [129]. The JBL PRO SCAN freshwater test kit includes a water test strip designed to test freshwater aquariums, ponds, and tap or well water by having the water test strip analysed by a smartphone. However, the JBL kit was not designed to test water quality for human consumption. It was primarily designed for monitoring water parameters in freshwater aquariums to ensure a healthy environment for fish and aquatic plants. The guidelines and parameters used in this test kit are, therefore, only tailored for aquarium water quality management rather than human drinking water standards [129].

Although there are no independent studies and data available yet on the performance of the mobile application, as it relates to accuracy and reliability, due to how recently it was launched, the information provided by the company is the best source for evaluating the accuracy of the application. The information on the company's official website indicates that in at least one case – nitrite testing— the application may show variability. The recommendation for an additional drop test measurement using the JBL PROAQUATEST NO2 Nitrite test indicates that users should exercise caution and verify the nitrite levels independently if the ProScan result does not show 0. Therefore, the need for an additional test suggests that the nitrite measurement with the ProScan may not be consistently reliable, and users should consider supplementary testing for critical parameters such as nitrite [129, 130].

Another element that can be evaluated is the accessibility of the entire test kit, including the application, due to its cost. The kit costs between R480 and R630, depending on the distributor used [131, 132]. With the top 10% of South Africans owning 86% of the country's total net wealth, while the bottom 50% have a negative net worth, the extreme inequality in wealth distribution highlights the financial challenges faced by the majority of households, as noted in the study by the United Nations University World Institute for Development Economics Research (UNU-WIDER) [133]. To stress the low income being made by the majority of the country compared to the cost of living in the country at the time, the UNU-WIDER had the following to say: "These results flag the precarity of the majority of individuals

with low or negative net worth. Policy-makers should urgently direct attention to policies enabling greater security to the general population." [133].

6.4 Benefits of Colourimetric Analysis: Comparing Traditional Methods

A comparative analysis between integrated systems and traditional water quality assessment methods brings to light the significant advantages of automated methods. Conventional approaches to monitoring water quality typically entail intermittent sampling and lab assessments, which can be lengthy and may lack immediate insights. In contrast, the incorporation of AI makes possible ongoing, real-time analysis and early identification of pollutants [134].

Moreover, the automated nature of object detection and colourimetric analysis reduces human error and variability, leading to more consistent and objective results. Additionally, the real-time capabilities of these systems enable timely decision-making and response to water quality issues, enhancing overall monitoring and management strategies. A study by Behmel et al. evaluated existing approaches to planning and optimising water quality monitoring and highlighted the efficiency gains and accuracy improvements of integrated systems over conventional methods, concluding the advantages of dynamic monitoring systems that can potentially enable timely and comprehensive decision-making support [135].

A study evaluating paper-based analytical devices (PADs) combined with colourimetric detection and the use of smartphone imaging demonstrates how increasingly popular this technology is becoming due to their versatility in various measurement applications [136]. The study evaluated four machine learning (ML) models – logistic regression, support vector machine (SVM), random forest, and artificial neural network (ANN) – along with three image colour spaces (RGB, HSV, and LAB) to predict analyte concentrations from images of PADs [136]. ML models showed higher accuracy in food colour assays than enzyme inhibition assays, especially in coarse-level classifications. Integrating sample colour with a reference colour significantly improved prediction accuracy, addressing variations from ambient conditions. The best-performing combinations were ANN with LAB colour space for food colour assays (accuracy of 0.966) and SVM with LAB colour space for enzyme inhibition assays (accuracy of 0.908). These findings highlight the benefits of using ML models and specific colour spaces for accurate and efficient field-testing using PADs [136].

Similarly, Mutlu et al. [137] explored machine learning for smartphone-based colourimetric pH detection using strip images. The authors trained least-squares support vector machine (LS-SVM) classifiers, achieving accurate pH level identification despite image format variations and lighting changes. Test results showed high accuracy and adaptability, making this method promising for smartphone-based colorimetric assays [137]. These case studies exemplify the versatility of integrated systems in addressing diverse water quality parameters.

7 Conclusion

In summary, this literature review extensively explored various dimensions of water quality assessment, starting from a global outlook down to regional perspectives and technological advancements. The legal frameworks governing water quality assessment, both on an international scale and within South Africa, illustrate the regulatory landscape required for effective monitoring and management. This understanding of legal aspects ensures that assessments are conducted in adherence to standards and guidelines, ensuring the reliability and validity of the results.

A thorough examination of South African water quality, including regional evaluations and public perceptions, reaffirms the necessity for reliable monitoring systems. The challenges faced, such as deteriorating water quality and inadequate infrastructure, emphasise the pressing need for technological

interventions. Emerging real-world technologies and their applications offer scalable solutions, from data collection and analysis to automated monitoring systems, improving current measures implemented for water quality management.

The focus on colourimetric analysis in this review stresses its benefits when the process is automated as compared to traditional methods, demonstrating its effectiveness in rapid, on-site testing. By leveraging industry standards and advancements in colourimetric analysis, water quality parameters can be identified accurately, leading to proactive and informed decision-making in water resource management.

In essence, this literature review reiterates the gap left in the market as well as the growing need for a mobile, inexpensive water testing tool, using techniques such as machine learning, computer vision, and colourimetric analysis that are capable of evolving with the population and the water assessment landscape. The instances where these technologies have been implemented, the results of the studies or impacts of deployed applications have demonstrated that an AI-based water quality assessment application can pave the way for sustainable water management practices in South Africa and enable water quality mapping in both urban and rural regions.

Chapter 3: Research Methodology and Design

1 Introduction

This chapter outlines the research design, data collection, and analysis techniques aimed at improving water quality monitoring. It will discuss the overall approach to the study, including the selection of water samples, the integration of computer vision for image analysis, and the application of machine learning algorithms for data interpretation. The chapter will also detail the methods used for validating results, ensuring accuracy, and addressing potential challenges encountered throughout the process.

2 Brief Overview of the Research Project

2.1 Description of the Smartphone Application

As previously stated, the research project focuses on developing a smartphone application to assess water quality. The application enables users to capture images of water test strips using their smartphone camera and subsequently analyse these images to provide predictions regarding the safety of their drinking water. The application seeks to provide users with real-time predictions regarding the quality of their water. One of the distinguishing aspects of this problem lies in its intersection with the development of analytical software, image analysis, and water quality assessment. The mobile application is divided into frontend and backend development with the analytical software being primarily incorporated into the backend algorithm. The mobile application does not function in isolation but stores information in a database developed specifically for this application and the water quality results are displayed on a live map embedded into a web application.

2.2 Methodology Focus

The methodology of the backend algorithm of the development process centres around two primary technical areas of the software development process: image analysis and data processing. This involves designing and constructing an algorithm that can receive an image, process the image by applying colourimetric techniques using object detection and CV, and then send the outcome to both the application database and the frontend of the application. More specifically, the image analysis component entails the interpretation of the captured water test strip images and extracting relevant features from the image which is used to infer information about water quality. The frontend consisted of the user interface (UI) design. This component of the software must allow the user to navigate through the application, capture and send an image to the backend, and then automatically retrieve the results in a manner that the user can easily interpret.

In developing this system, it is essential to address the research questions of the study. Thus, the methodology must assess the role of object detection using machine learning, alongside the image analysis and processing steps, to interpret the results and determine the reliability of the algorithm in accurately measuring water quality parameters.

3 Purpose of the Research Methodology Chapter

3.1 Insight into the Methodological Approach

The purpose of this chapter is to provide a comprehensive overview of the methodological approach adopted in the development and evaluation of the smartphone-based application. This includes detailing the research design, data collection methods, data analysis techniques, and reliability strategies employed throughout the research process. Furthermore, the chapter also discusses the research design, which adopts a descriptive and interpretive case study approach analysed largely through quantitative methods. This approach facilitates a nuanced understanding of the application's functionality.

3.2 Justification of Selected Methods

Additionally, the chapter aims to justify the selection of specific research methods in alignment with the research objectives. It offers insights into why certain methodologies were chosen over others and how they contribute to achieving the desired outcomes of the research project and answering the research questions while operating within the scope of the study. Central to this is the exploration of design assumptions and research strategies that underpin the study, setting the stage for an examination of the software development journey and its implications for water quality assessment. At the outset, this chapter addresses fundamental assumptions inherent in the research methodology, including considerations related to mobile network coverage, user accessibility to smartphones, and data storage capacity of a near real-time mobile and web application. These assumptions inform key decisions regarding the design, development, and implementation of the water monitoring application, emphasising the need for pragmatic solutions to address potential challenges.

4 Significance of Methodological Choices

4.1 Implications for Study Validity and Reliability

The methodological choices made in this research project have significant implications for the validity and reliability of the study findings. The research methods discussed in this chapter were used to ensure that the methodology is not only valid but appropriate for the development of the application in the given setting to address the study objectives. By carefully considering various research methods and techniques, the research aims to ensure the accuracy and credibility of the results obtained.

5 Project Overview and Key Objective

The main objective of the study is to evaluate the effectiveness of the developed smartphone application in accurately assessing chemical water quality parameters. The application's input is an image of the water test strip. This input is analysed and segmented using a supervised ML model and CV techniques to identify the features of interest. The application then conducts a colourimetric analysis of the water test strip. The system interprets the results, logs the location of the test sample through geotagging, and generates a water quality assessment report. This information is stored in a database. The water quality assessments determine the overall safety of the sample for drinking. These results are then used to map the country's water quality by creating a profile of the water bodies across the nation as the system receives more water quality assessment. The aim is that when this data is mapped, it allows users to better understand this tool's usefulness, leading to further and more regular water testing. This is demonstrated in Figure 3.1.

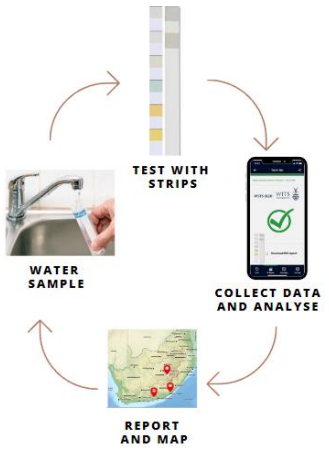


Fig. 3.1 Cycle of water testing

6 Research Paradigm and Design Approach

To provide a better understanding of the design protocols, the underlying research philosophies and the research type deployed for the software development and analytical techniques used must be discussed. The research philosophy also aids in identifying the structure of the study. The two most relevant paradigms that have been identified for this study are positivism and pragmatism.

6.1 Positivism

Positivism prioritises practical observation and the systematic application of scientific principles. It centres on the impartial assessment of quantitative techniques to assess the performance of the water quality assessment system. In the context of developing a smartphone application for water test strip analysis, adopting an approach that emphasises empirical observation and the scientific method through implementing techniques such as machine learning in the form of object detection, computer vision, and colour classification, results in the more accurate analyses of the strips to determine chemical levels. Metrics such as precision, recall, and F1-scores gauge the application's reliability.

6.2 Pragmatism

Pragmatism focuses on tangible results and applications in real-world scenarios. It is well-suited for this research which aims to resolve a practical problem with the guide of specific requirements. On a technical front, a pragmatic stance entails not only evaluating the theoretical efficacy of the software behind the application but also addressing practical concerns such as user-friendliness, scalability, and integration within the mobile application ecosystem. By prioritising real-world applications and tangible outcomes, this pragmatic attitude ensures that the developed application effectively serves its intended purpose to users.

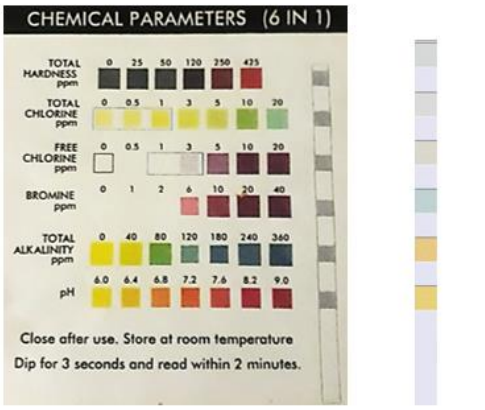
6.3 Research Design Type and Associated Assumptions

The research design method is a strategy of inquiry, which progresses from the underlying assumptions to the research design, and to the data collection [138]. In this study, the research design type is relevant to the data collection techniques, analysis, data validation, and testing, and, finally, presentation to the users. The focus of the research question is the use of qualitative or statistical results as opposed to descriptive data to determine the success of the study. Although this study primarily uses quantitative methods in both design and implementation, some qualitative data received in the form of feedback during testing plays a role in the overall evaluation of the success of the study and its ability to meet the predicted social impacts. Therefore, a mixed methodology – both qualitative and quantitative – is used.

7 Data Collection

7.1 OUTA Water Test Strip

The data used for this investigation is images of a 6-parameter water test strip. The strip is manufactured by iLabs and is being provided by OUTA, as part of their water test kit. The six parameters being tested through chemical patches on the test strip are total hardness, total chlorine, free chlorine, bromine, total alkalinity, and pH. It can, therefore, only indicate the chemical profile of the water sources being tested. To manually analyse the results of a water test conducted using the strip, the water test strip seen in Figure 3.2 (b) will be used in conjunction with the colour card shown in Figure 3.2 (a).



(a) colour card (b) test strip

Fig. 3.2 OUTA colour chart with chemical water test strip

7.2 Data Collection Techniques

Data for the training and validation of the ML-based object detection algorithm and the validation of the model were obtained in two main manners. The first is through images captured of the water test strip using a smartphone by the developer and through a citizen science campaign. The campaign was led by the partnering organisation – OUTA – through their WaterCAN initiative across the country. The campaign ran from August to September 2023 and relied on citizens testing their water quality using the OUTA test strips and then capturing the images of the strips against a template of the water test analysis colour chart on their mobile devices, and uploading the images to the OUTA website. The samples were taken at various locations, from different sources and captured under different physical conditions. This data set had to be representative of the real-world images the application will be exposed to when it is deployed. Images were also taken in a laboratory setting with controlled physical conditions. This is to allow for images to be taken under ideal conditions, to assist in the machine learning model training process. This is further discussed in the machine learning section. This two-pronged technique also provided a control to compare images during the pre-and post-processing stages of the software development.

Ultimately, the model's data requirements guided the data collection process, along with the permissions granted by the ethical clearance provided by the University for the study. Approximately four thousand images were obtained as raw data. After removing images that were unsuitable to use in the processes listed above, three thousand images remained. After data augmentation techniques were applied, which refers to the process of artificially increasing the diversity of a dataset by applying transformations such as rotation, scaling, or flipping to images, aimed at improving the generalisation of the ML model [139], the sample size of the images was increased to seven thousand images.

8 Backend Software Development – The Analytical Engine

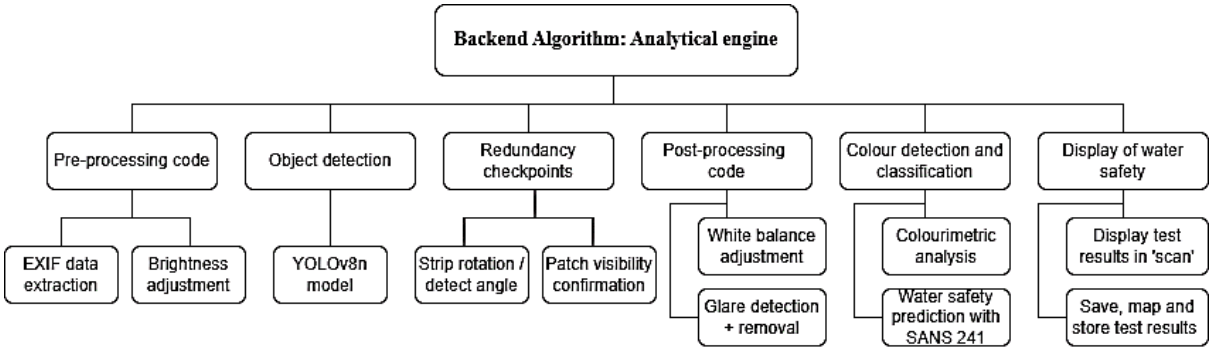


Fig. 3.3 Overview of software architectural hierarchy

The study uses colourimetric analysis of the water test strip images as one of its key analytical tools. The retrieval and display of these results on users' mobile device screens necessitate a structured software development protocol. Adherence to this protocol is essential for creating a high-quality smartphone application capable of consistently analysing water test strip images and delivering accurate results to users, while anticipating common software pitfalls when dealing with image-based analysis. The development protocol summarised consists of the following stages: the input to the application, image processing, machine learning-based object detection, colour classification and water quality prediction. Figure 3.3 visually demonstrates the hierarchy of the code segments that handle the different tasks in the analysis of the input of the application to achieve the goal of providing the user with accurate and timely water quality results.

8.1 Development Protocol

8.1.1 Application Input

The first step in the programme sequence is the input to the application, which is the image of the water test strip. This image is uploaded to the programme, and is stored locally during development, so information regarding the type of image being uploaded and details of the upload conditions are known. However, once deployed, the user will be capturing the image on their mobile device once they have opened the application. Therefore, very little information about the condition of the physical environment will be known, nor the specifications of the mobile device. To account for this, the images are automatically processed to ensure consistency when received by the software program. First, the images are resized. The resizing of the image to a standard resolution removes any unnecessary components of the image. Secondly, further techniques are implemented as a control check through the user interface, to aid in verifying the integrity of the colours of the acquired image which will be discussed in the following section of the chapter. Images that do not meet the predefined standards set forth for the analysis are automatically rejected and the user will be asked to capture another image of the strip. The image pre-processing, object detection, and image post-processing tasks will further the process of determining the quality of the uploaded image, and whether it is suitable for analysis.

8.1.2 Image Pre-processing

The image pre-processing is crucial for ensuring the accuracy and reliability of the water quality assessment process. It does this by isolating metadata associated with the image that provides details on the device used to capture the image, the physical environment such as the time of day and location of the user at the time the image was captured and it gives insight into what types of further processing may need to be applied to the image. Artifacts such as shadows are removed by brightening the image.

Noise reduction through filtering the image is performed so that necessary features are visible. This process comprises two main stages: EXIF data extraction and image brightening.

8.1.2.1 EXIF Data Code

This code segment performs EXIF (Exchangeable Image File Format) data extraction from an uploaded image, a crucial step in gathering metadata associated with the image. Upon successful upload of the image to the application, the code uses the Pillow (PIL) library [140] and its EXIF processing capabilities to extract metadata stored within the image file. The metadata includes camera settings, timestamps, and, most importantly for this application, Global Positioning System (GPS) coordinates. These coordinates are vital for linking the water quality test results to specific geographical locations, aiding in mapping water quality across South Africa.

The `extract_metadata_from_image()` function begins by attempting to open the image file and safely handles any errors during this process. Using the `getexif()` method, the function retrieves the EXIF data, iterates through it, and converts tag numbers to their corresponding names using the ExifTags.TAGS and ExifTags.GPSTAGS mappings. Values are converted to string format to ensure compatibility with JSON and other processing steps.

If GPS-related information is present, it is extracted and organised into a nested dictionary for clarity. The metadata, including GPS information if available, is saved to a text file named `metadata_imported2.txt` for testing and further analysis. The function also returns the metadata as a dictionary, allowing for additional programmatic use such as passing the GPS data to Firebase. This enables the application to associate each water quality test result with its corresponding geographical location, contributing to broader environmental monitoring efforts. The flowchart in Figure 3.4 illustrates this process.

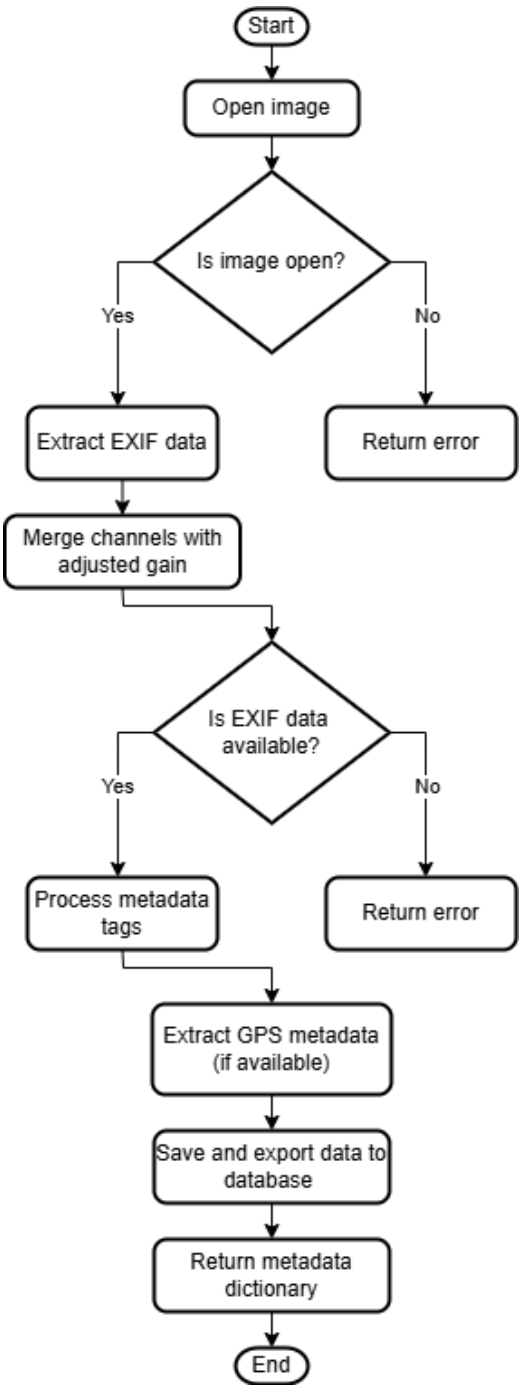


Fig. 3.4 EXIF data flowchart

8.1.2.2 Brightness Adjustment Code

The brightness adjustment code optimises the visibility of a water test strip in an image, ensuring consistent results in subsequent processing steps such as object detection and colour analysis. It uses the OpenCV (`cv2`) [141] library for image manipulation and the PIL library for brightness enhancement. This step is crucial for standardising brightness levels in uploaded images, particularly under varying lighting conditions. The process begins by converting the input image to grayscale using OpenCV's `cvtColor()` function, which simplifies the brightness analysis by removing colour

information. The mean brightness of the grayscale image is calculated and normalised to a value between 0 and 1. A minimum brightness threshold is applied to prevent the mean brightness from falling below an acceptable level, avoiding overly dark images.

An adjustment factor is computed by dividing the target brightness by the normalised mean brightness. To prevent excessive adjustments, this factor is constrained within a defined range using a threshold parameter. Specifically, the adjustment factor is capped at a minimum of 1 - threshold and a maximum of 1 + threshold, with an upper limit of 1.5 to maintain natural image quality. The enhancement itself is performed using PIL's `ImageEnhance.Brightness()` class. The input image, converted from OpenCV's NumPy array format to a PIL image, is adjusted using the computed factor. After enhancement, the image is converted back to NumPy array format using OpenCV for further processing or saving. This streamlined brightness adjustment ensures that the image preprocessing phase creates standardised and visually consistent images, facilitating accurate downstream tasks.

8.1.3 Object Detection

Object detection is central to this system, providing the means to identify and locate essential features on water test strips. The subsequent sections outline the development, training, and deployment of the detection model, underlining its application to real-world water quality testing scenarios.

8.1.3.1 Machine Learning Framework

YOLOv8 Model Overview. The YOLO (You Only Look Once) [142] algorithm used in this study stands out as a prominent object detection algorithm, well known for its real-time detection capabilities. YOLO version 8 (YOLOv8) is a deep learning-based object detection algorithm that predicts bounding boxes and class probabilities directly from images. Unlike traditional detection methods that rely on region proposal algorithms, YOLOv8 performs detection in a single pass, making it significantly faster and more efficient. YOLOv8's efficiency and accuracy make it well-suited for real-time detection tasks, making it an ideal choice for applications requiring rapid processing of visual data.

Creating the Training Dataset. To train and test the model, a dataset of annotated images of water test strips is collected from different water samples. The two main sources – laboratory testing under ideal conditions and the OUTA WaterCAN initiative from across the country – were discussed in the data collection section. The training set consists of the water test strip dataset curated and described in Section 2 of this chapter, which was collected under diverse conditions, such as varying lighting, backgrounds, orientations, and camera qualities. A large and diverse dataset is essential for training the YOLOv8 model to ensure good generalisation across various scenarios and object classes. This assists the model's ability to learn a wide range of features and patterns, improving its ability to accurately detect objects in real-world images. The original dataset is split into an 80/20 ratio, with 80% of the data being used for training the model and 20% for training validation [143].

Data Preparation. Before training, the images undergo pre-processing, which includes resizing them to a standard size to ensure uniformity. Data augmentation techniques are also applied to increase the diversity of the training dataset, enhancing the model's ability to generalise to unseen data. The dataset is then labelled using the LabelImg tool [144], where bounding boxes are drawn around the six square patches and the strip itself – the objects of interest – and class labels are assigned. After labelling, the data set is then shuffled to reduce variance and avoid overfitting. Shuffling the dataset ensures that the training process is not biased by any specific ordering of the data. While it helps reduce variance in the sense of preventing localised patterns from dominating the training process, the primary goal is to avoid overfitting by exposing the model to a diverse representation of the data in each batch [145].

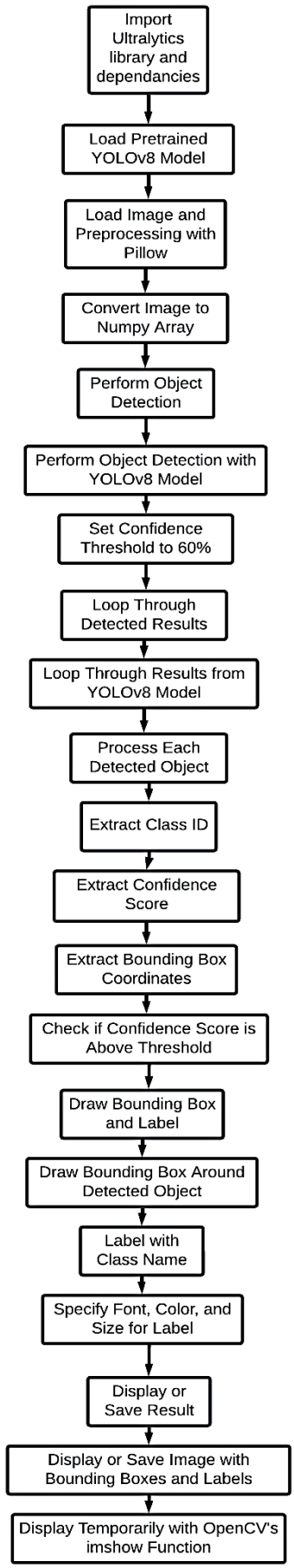


Fig. 3.5 YOLO model framework and implementation

Model Setup and Initialisation. With the data preparation complete, the YOLOv8 model architecture is configured. This involves defining the model's layers, parameters, and initial weights to establish the foundation for training. Standard parameters were configured following the Ultralytics guide, providing a reliable framework to ensure optimal performance and adherence to best practices. The setup process, when done correctly, enables the model to learn effectively from the dataset while maintaining adaptability for diverse scenarios.

YOLOv8 Training Process. To train the YOLOv8 algorithm, the labeled dataset consisting of images and corresponding annotations are fed into the code. During training, the model learns to predict bounding boxes and class probabilities for objects within images by minimising the defined loss function. This involves an iterative process where the model learns to recognise patterns and features that differentiate between the separate predetermined classes. During training, the model is assessed to confirm that losses are minimised using a predefined loss function that measures the discrepancy between predicted and true labels. Intersection over Union (IoU) is the metric used to measure the overlap between predicted and ground-truth bounding boxes [146]. Along with the six chemical indicators and the test strip, the model also detects two additional classes, 'rotated strip' and 'upside-down strip', which are also bounding boxes drawn around the test strip but helps to identify the orientation of the strip. The bounding boxes drawn around the detected objects, provide spatial localisation information which is stored and fed into the next code segment to connect each bounding box, with its class label to the colour detected and its associated contaminant information during the classification task.

Training Considerations. Key factors such as lighting conditions, camera quality, strip orientation, and background variations are accounted for during training to simulate real-world scenarios and enhance the model's capacity to generalise. Incorporating these variations ensures that the model can accurately detect all bounding boxes under diverse conditions. To address these considerations, the model undergoes continuous customisation, informed by regular reviews of its most recent validation outcomes.

Model Customisation and Training Parameters. The YOLOv8 nano algorithm – also referred to as only the YOLO algorithm – is implemented and customised using Python within the PyCharm [147] integrated development environment (IDE). Training parameters, such as the number of epochs, learning rate, and batch size, are fine-tuned through iterative experimentation to optimise the model's performance. The final batch size is set to 32, with 50 epochs of training to obtain results that met the test threshold. A threshold of 0.6 is set to ensure accurate detection by requiring sufficient overlap between predicted and actual objects.

Validation of Trained Model. Once the model has been trained, it undergoes evaluation. Validation data, which is distinct from the training dataset, is used to assess the model's performance and ensure

its ability to generalise effectively. This process confirms that the model functions as intended and identifies opportunities to optimise its training procedures and outputs. Quantitative metrics, including precision, recall, and mean average precision (mAP), are employed.

8.1.3.2 Object Detection Implementation

Once trained, the YOLOv8 model is implemented. Firstly, the pre-trained model is loaded from the specified path, followed by loading the image using the Pillow library and converting it to a NumPy array using OpenCV. For convenience, all libraries used in the code are listed in Appendix 3.1. Object detection is then performed on the image using the loaded model. The model then performs inference on the new, unseen image. For each image, the model detects objects and their corresponding bounding boxes and labels. If the confidence score exceeds the threshold, bounding boxes are drawn around the detected objects, and labels are added to indicate the class of each object. Finally, the result, including the prediction values, and bounding box information is displayed and saved, with the option to visualise the object detection outcome for each image. The model also generates graphs and visualisations to display the model's performance metrics which are discussed in Chapter 4. A block diagram of the approach and implementation of the YOLO model is shown in Figure 3.5.

8.1.3.3 Non-Maximum Suppression

Non-maximum suppression (NMS) is a post-processing technique used in object detection models, such as YOLOv8, to refine predictions. In this study, NMS is implemented to prevent the YOLOv8 model from generating multiple bounding boxes for each predicted object, particularly under non-ideal conditions, based on different features and confidence levels. It ensured the accurate detection of chemical patches on test strips by eliminating multiple overlapping bounding boxes for the same object. This is done by calculating the IoU between bounding boxes and suppressing all but the one with the highest confidence score.

In this project, the `non_max_suppression()` function eliminates redundant bounding boxes by comparing their overlap using the IoU metric, calculated by the `calculate_iou()` function. The algorithm sorts bounding boxes by their positions and iteratively selects the one with the highest confidence while discarding others that exceed the overlap threshold. By retaining only non-overlapping or minimally overlapping boxes, this process improves detection accuracy and reduces noise in the results. By maximising the IoU score and applying NMS, the system reduces false positives and enhances detection precision, thus refining the object detection model's outputs.

8.1.4 Redundancy Checkpoints

The software programme also includes redundancy checkpoints. This code serves as additional mechanisms implemented and acts as a failsafe. This failsafe is to enhance the fault tolerance of the application. This allows for the optimal application of the analytical techniques deployed by the programme. It does this by detecting and overwriting errors in the previous stages of the programme sequence that may result in faulty or inaccurate information being passed onto the colour classification code.

In particular, techniques like thresholding and edge detection are used to segment the test strip from the background, and the strip patches allow the application to identify the presence of the regions of interest (ROIs). Some test patches on the strip may be faint or partially obscured, making them difficult to analyse accurately. Processing methods such as contrast enhancement and adaptive thresholding enhance the visibility of these patches, improving their detectability for analysis, when the key detection

method implemented in the main flow of the code fails. This process comprises two main stages: strip orientation confirmation through angle detection and Sobel edge detection for patch confirmation.

8.1.4.1. Confirm Orientation – Rotation Angle Code

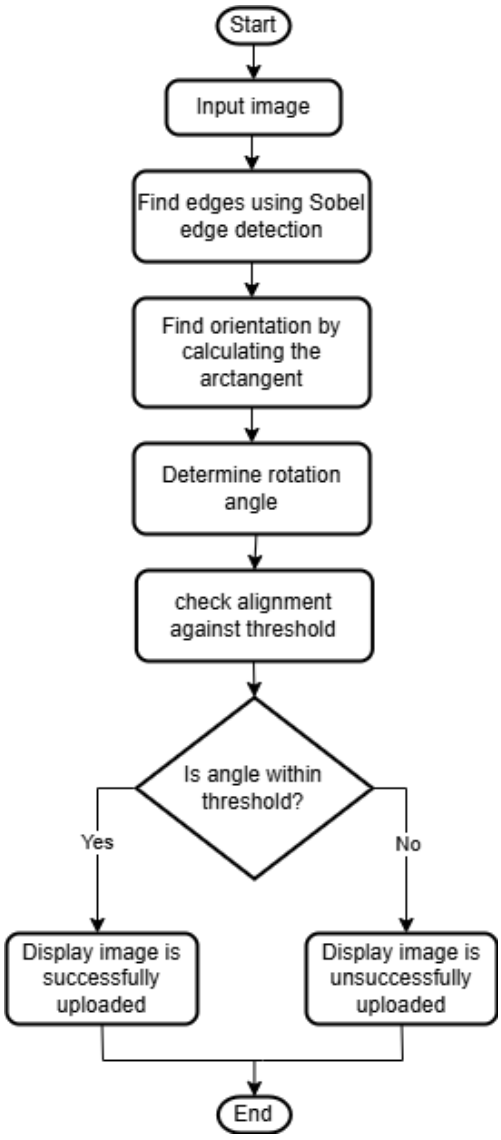


Fig. 3.6 Rotation angle detection code flowchart

This code segment is responsible for determining the orientation angle of the water test strip within an uploaded image if the object detection is unsuccessful in determining the orientation of the strip. This serves as a redundancy measure to ensure the correct alignment of the strip, complementing the orientation determination performed by the object detection model. The code functions by analysing the edges of the image and calculating the orientation angle numerically. Firstly, the `findEdges()` function uses the Sobel edge detection algorithm [148] to identify edges within the image. These edges serve as key indicators for determining the orientation of the strip. Subsequently, the `findOrientation()` function calculates the orientation of the edges, yielding a numerical representation of the strip's angle within the image. Once the orientation is determined, the `determineRotationAngle()` function computes the angle required to rotate the image for perfect alignment, either vertically or horizontally (0 or 90 degrees). This angle is essential for ensuring that the strip is correctly oriented within the image frame.

To validate the alignment, the `checkAlignment()` function compares the calculated rotation angle to a predefined threshold, allowing for a tolerance of 5 degrees in either direction. If the deviation from the desired orientation falls within the threshold, the programme proceeds with the assumption that the strip is correctly aligned. Otherwise, a message prompts the user to reposition the strip and retake the image. The `generalPipeline()` function orchestrates the entire orientation detection process, including image preprocessing, edge detection, orientation calculation, and alignment verification. Upon execution, the function displays the input image along with diagnostic information such as the rotation angle and alignment status. Figure 3.6 visually demonstrates the above sequence.

8.1.4.2 Patch Detection

Following the preprocessing and orientation determination steps, the accurate detection of the six test patches becomes essential to ensure the reliability of subsequent analysis and interpretation. The `check_all_patches_detected()` function has been designed to verify the presence of the required test patches, which include total hardness, total chlorine, free chlorine, bromine, total alkalinity, and pH. This function eliminates the need for template matching and instead directly evaluates the detected patch data, allowing for a more streamlined approach.

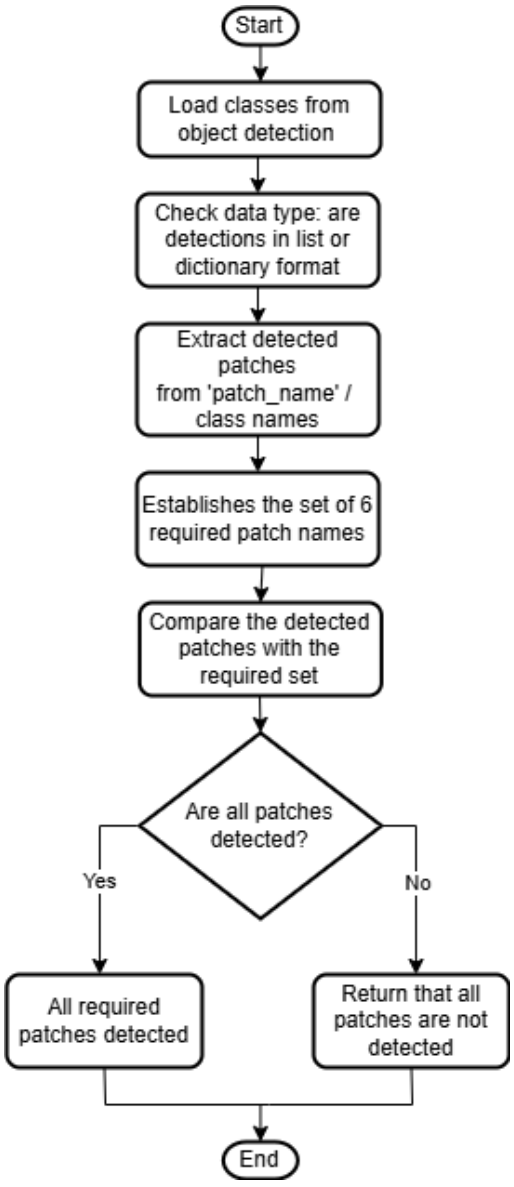


Fig. 3.7 Patch visibility code flowchart

The input data provided to the function may take the form of either a list, typically derived from results generated by colour analysis processes, or a dictionary containing raw patch data. The function adapts to the input format accordingly. In the case of a list, it extracts the names of the detected patches from the 'patch_name' field. Conversely, when a dictionary is supplied, the patch names are retrieved from the dictionary's keys.

The function then compares the detected patches against a predefined set of required patch names to ensure that all necessary patches are accounted for. A set-based comparison is employed to determine whether the detected patches include all the required elements. Debugging logs are used to display the detected and required patch sets, thereby enabling the verification of the detection process during development and testing.

The function concludes by returning a boolean value. A return value of True indicates that all required patches have been successfully detected, while a return value of False signifies those one or more patches are missing. This approach ensures a robust and efficient mechanism for the detection of the test patches, which is crucial for ensuring the accuracy and validity of the subsequent analytical processes. The overall process is depicted in Figure 3.7.

8.1.5 Image Post-processing

The image post-processing codes are so named as the first role it serves, when viewing the code sequence in chronological order, is to process and store the information received from the previous stages in the software development protocol. This information is then processed to provide the first stages of the remaining image-processing tasks.

However, another vital role these code segments serve is to prepare the incoming image for the colour classification task. It does this by standardising the image characteristics. As the water test strip images may vary in terms of lighting conditions, camera settings, and overall image quality, processing techniques such as histogram equalisation, colour correction, and white balancing can standardise these characteristics, ensuring consistency across different images. Artifact removal such as glare or reflections that may obscure or distort the appearance of the test patches are identified and removed. Colour space conversion is also performed to facilitate colour-based analysis of the test patches to help extract meaningful colour information from the patches while minimising the impact of variations in lighting conditions. The relevant code segments involved here is the white balance code and the glare detection and removal codes.

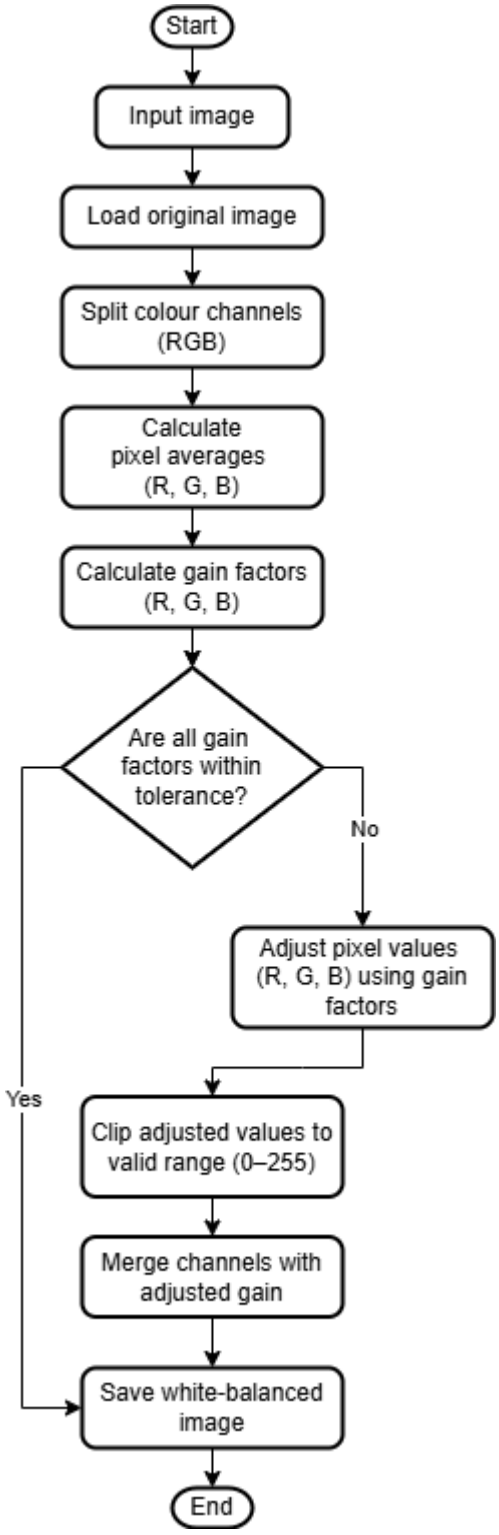


Fig. 3.8 White balance code flowchart

8.1.5.1 White Balance Code

A white balance procedure is needed before conducting colour detection and classification tasks to ensure accurate and consistent colour representation across different lighting conditions and environments. In the provided code segment, the `perform_white_balance()` function implements a simple Gray World [149] white balance technique to adjust the colour balance of the input image.

The function begins by splitting the input image into its red, green, and blue channels using the `cv2.split()` function. It calculates the average pixel intensity for each channel and then computes the overall average intensity across all channels. Gain factors for each channel are determined by dividing the overall average by the average intensity of the respective channel. This ensures that the intensity levels of the channels are balanced relative to one another.

To apply the adjustments, each channel is multiplied by its corresponding gain factor, with pixel values clipped to ensure they remain within the valid range (0–255). The adjusted channels are then merged again using `cv2.merge()`, producing a white-balanced image where colour casts are corrected to achieve a neutral balance.

The function includes a tolerance parameter, which checks whether the gain factors for all three channels are sufficiently close to 1. If they are within the specified tolerance, the original image is returned without modification. This avoids unnecessary adjustments to already balanced images. The input to the `perform_white_balance`() function is the original image captured by the smartphone camera, while the output is the white-balanced image with corrected colour tones. This preprocessing enables accurate colour extraction and classification in subsequent processing stages, as seen in Figure 3.8.

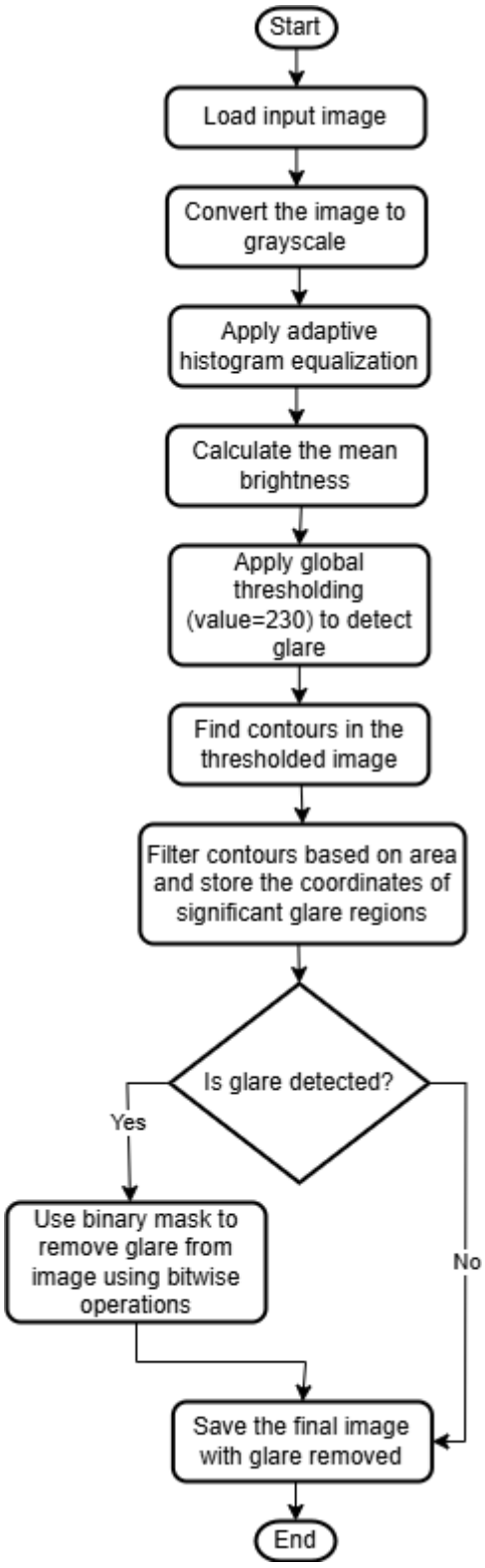


Fig. 3.9. Glare detection and removal code flowchart

8.1.5.2 Glare Detection and Removal

In image processing, glare refers to intense and bright light reflections or sources in an image that can significantly hinder the accuracy of subsequent image analysis tasks. Glare often appears as regions of white light, leading to overexposure and saturation of pixel values in the affected areas. Detecting and removing glare is essential to ensure the accurate identification and analysis of image features, particularly for colour identification tasks where precise pixel values are critical.

This code segment includes functions for detecting and removing glare to minimise its impact on colour extraction and classification tasks. In the `detect_glare()` function, the input image is first converted to grayscale, followed by local contrast enhancement using Adaptive Histogram Equalisation (AHE) [150] to improve the visibility of glare. The function identifies glare based on the mean brightness of the enhanced image exceeding a specified threshold `(glare_threshold)`. Contours are then extracted to delineate glare regions within the image, and significant glare areas are identified by filtering out small regions based on their size. If glare is detected, the `process_glare()` function is invoked to process the ROIs containing glare. This involves applying an inverted binary mask to isolate and remove glare from the image. If no glare is detected, the programme skips additional processing, optimising computational resources by only applying glare removal when necessary.

The `remove_glare()` function combines these steps to implement the glare removal procedure. It detects glare in the input image using `detect_glare()` and processes the glare-affected areas using `process_glare()`. If no glare is found, the original image is returned unmodified. The glare removal algorithm shown in Figure 3.9 ensures that glare artifacts are effectively eliminated from the input image, facilitating accurate colour extraction and water quality analysis. Libraries such as OpenCV and NumPy are employed for image processing tasks, including grayscale conversion, thresholding, and contour analysis. The final glare-free image enables reliable colourimetric analysis, enhancing the accuracy of subsequent water quality assessments.

8.1.6 Colour Detection and Classification

8.1.6.1 Classification Approach

The colour detection and classification methods deployed for this application has one key objective – to accurately identify different contaminants present in the water samples based on the colour changes observed on the test strip. The colour is interpreted by the algorithm by determining which of the predefined colours are the closest in pixel values to the detected patch colour. Predefined colour ranges are established based on known standards and guidelines for water quality testing.

The predefined colour ranges serve two main purposes: to simplify the interpretation process and as a quality control measure. Predefined colour ranges simplify the interpretation of test strip images by reducing the complexity of colour analysis. It also mitigates the risk of misinterpretation or misclassification of colour changes on the test strips. By flagging results that fall outside the predefined ranges, the application can identify potential errors or anomalies in the analysis process, which could include the system attempting to analyse an unused strip.

This quality control mechanism help maintain the integrity of the data generated by the application and enhance confidence in the accuracy of the results. By adhering to these ranges, the application can provide accurate and reliable results. This serves as safety guardrails to prevent adverse consequences associated with incorrect results, which is in line with the ethical requirements of this study. This technique automates the process of analysing the water test strips, eliminating the need for manual interpretation and subjective judgment. The application provides objective and consistent results, reducing the potential for human error and ensuring accuracy and reproducibility. This technique provides a step-by-step method to implement the classification process while ensuring that there are safety measures built-in to the programme to limit inaccurate results being passed onto the user.

8.1.6.2 Colour Classification Code Implementation

This code segment leverages several specific libraries, functions, and techniques to enable colour extraction, detection, and classification within the context of assessing water safety. Notably, the OpenCV library and NumPy are instrumental in implementing advanced image processing functionalities, facilitating the analysis of colour attributes within captured images. Built-in functions from OpenCV such as `cv2.imread()` and `cv2.cvtColor()` are used to load the captured image and convert it from the default BGR colour space to the HSV (Hue, Saturation, Value) colour space. The colour classification method involves analysing the patches on the water test strips and matching them to pre-set HSV ranges, derived from RGB values obtained using a digital colour picker. These ranges form the basis for the classification and interpretation of chemical concentrations in the test strips. This conversion is done as it simplifies the process of colour analysis by decoupling colour information from luminance, leading to more reliable colour detection results.

Additionally, the NumPy library is employed for efficient numerical computations and array manipulation. Within the code, NumPy arrays are used to represent colour ranges in the HSV colour space, enabling comparison and calculation of distances between observed colours and predefined colour ranges. Functions from NumPy such as `np.array()` and `np.linalg.norm()` are employed to define colour ranges and compute Euclidean distances between the detected colour and the pre-defined colour ranges [151], respectively. By calculating the Euclidean distance between the detected colour and the predefined HSV values, the system can tolerate minor deviations in colour and still make accurate classifications. This feature is particularly important in real-world applications, where lighting conditions and other environmental factors may introduce noise into the image.

The key function `extract_dominant_colour()` extracts the dominant colour within a selected patch of the image using K-means clustering [152]. First, the function defines the ROI based on a

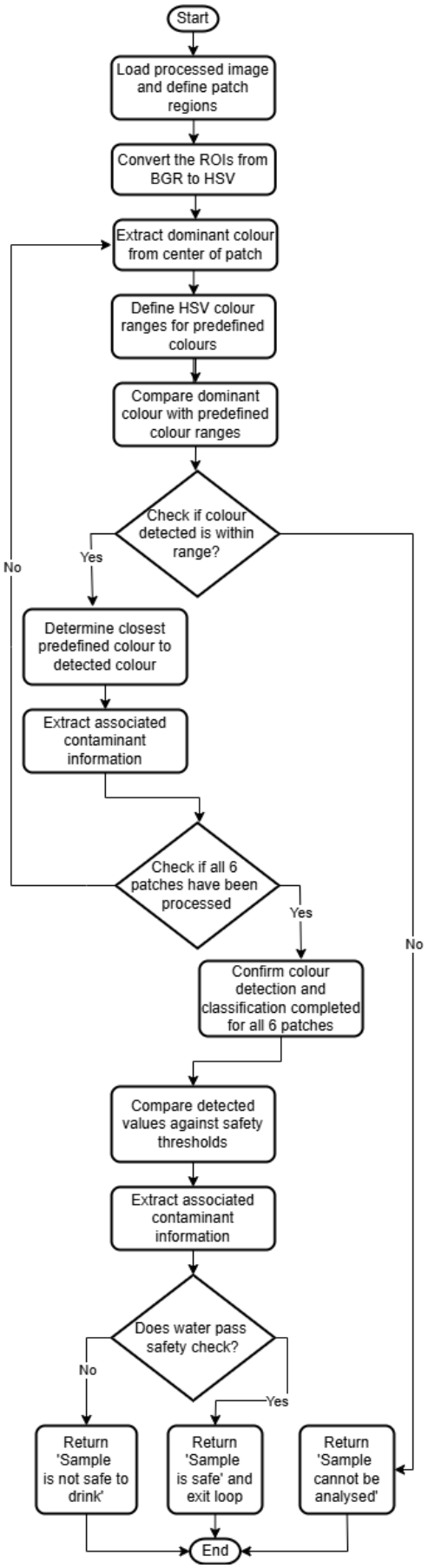


Fig. 3.10 Flowchart of the colour classification code segment

bounding box, focusing on the centre of the patch to simulate manual readings. The region is cropped, and the image is converted to the HSV colour space to facilitate more accurate colour analysis.

Next, the function applies K-means clustering, an unsupervised learning algorithm, to identify dominant colours within the selected patch. By clustering the pixels in the HSV colour space, the K-means algorithm groups the pixels into clusters, with each cluster representing a potential dominant colour. The centroids of these clusters are analysed to identify the most representative colour [152]. The `cv2.kmeans()` function from OpenCV is used to perform the clustering, which assigns a dominant colour to the ROI based on the most frequent or central cluster.

Once the dominant colour is identified, the function returns this colour as an RGB value, converting the extracted HSV colour back to BGR using `cv2.cvtColor()`. This BGR value along with the upper and lower HSV value ranges are then used in further analysis to compare it against predefined colour ranges and classify the patch's colour. The code implements iterative procedures to process each patch on the colour chart individually, demonstrating a structured and systematic approach to colour extraction and classification. Through iteration, the code extracts ROIs, applies colour extraction techniques, and compares observed colours to predefined colour ranges, ensuring comprehensive coverage of all patches and contaminants.

The final stages of the classification code that deals directly with the final result – which determines if the water is safe to drink – makes use of a `does_water_pass_check()` condition which plays the lead role in determining the overall safety of the water sample based on the detected contaminant levels. This condition aggregates individual assessments for each patch on the test strip, evaluating whether the detected contaminant concentrations fall within acceptable ranges. Each patch's associated contaminant and its corresponding safe concentration thresholds are predefined in the code. The condition iterates through the results for each patch, checking if the detected values exceed the established thresholds. If any patch indicates a contaminant level beyond the acceptable range, the `does_water_pass_check()` condition is set to 'false', signifying that the water sample is not safe to drink. Conversely, if all patches report contaminant levels within the safe thresholds, the `does_water_pass_check()` condition remains 'true', indicating that the water is safe for consumption. This condition encapsulates the core of the water quality assessment, synthesising individual patch analyses into a

safety evaluation, thereby providing users with a clear and actionable determination of water safety. A visualisation of this section of the code is displayed in Figure 3.10 above.

9 Frontend Software Development – The UI and UX

This section outlines the design and development approach for the UI of the mobile application, focusing on how its structure, functionality, and user experience (UX) are tailored to support water quality analysis. It details the framework and design choices that ensure a seamless and intuitive interaction between the user and the application's analytical backend.

9.1 System Design

This section examines the approach to the mobile application's user interface, outlining its structure, functionality, and the software frameworks and libraries employed to ensure an intuitive and efficient user experience for water quality analysis.

9.1.1 UI Overview

The user interface allows the user to interact with the analytical engine of the code, referred to in this report as the backend of the software. The UI of the mobile application is designed to provide users with a convenient and efficient way to analyse water quality. It has been designed, taking into account various components to optimise functionality and UX. The application comprises multiple screens and widgets, each serving a distinct purpose tailored to meet specific user needs. The frontend component of the development of the application is secondary to the backend algorithm. However, its development plays an irreplaceable role and therefore needs to be discussed.

The software framework used to develop the user interface is Flutter, with the code being written in Dart. Flutter was selected due to its ability to provide a high-performance, natively compiled application for mobile, web, and desktop from a single codebase, making it an ideal choice for cross-platform development targeting both iOS and Android devices [153].

The design employs core Material Design elements [153], such as modern buttons, cards, floating action buttons, and bottom navigation bars, to facilitate intuitive navigation and support essential actions, including capturing water samples, uploading images, and viewing test results. The primary function of the application lies in its ability to process images of paper-based test strips to evaluate water quality parameters. This process is powered by Flutter packages, including image_picker and camera [153], which enable the capture and management of high-quality images directly on the device. Custom Dart code is used to extract colours, segment distinct zones on the test strip, and enhance image quality to ensure reliable analysis under varying conditions.

The results of the analysis are presented in a straightforward format, combining numerical values with graphs and charts for better comprehension. A history section allows users to track water quality trends over time, with options to customise graphs based on the chemical indicators in this study. This feature enables users to monitor changes and draw comparisons across different testing periods. From a technical perspective, the application’s performance is optimised to handle high-resolution image processing while maintaining responsiveness across a wide range of devices. Flutter’s native compilation ensures efficient execution, particularly for computationally intensive tasks. By balancing image resolution and processing demands, the application is designed to operate effectively in diverse settings, with Android as its primary platform.

9.1.2 Architectural Framework

The framework of the user interface design can be conceptualised as the various screens the user will have access to on the application. The key screens this design develops are:

a. Splash Screen: This serves as the application's introductory interface, providing a brief visual transition while the application loads its core functionalities. This loading animation is of a water droplet slowly filling up.

b. Welcome Screen: This screen introduces the application to users and displays the name of the application, along with a welcome message and the logo. The log-in and sign-up buttons are also present along with the logos of the social media platforms that can also be used to log in without a native account, e.g., Facebook and Google.

c. Main Menu Screen: This is what the user sees once logged on. The main menu screen presents four main widgets – Scans, History, News, and FAQs – allowing users to navigate to different sections of the application.

d. Scans Widget: This guides the user through the scan function by instructing them on when and how to perform the test process and to then capture a picture of the test strip, upload the image, and receive analysis results.

e. History Widget: Keeps track of past tests/scans completed, organised by date and time. This also graphs out previous test results over time.

f. FAQs Widget: Provides users with answers to common questions about app usage and water testing processes.

g. News Widget: Displays relevant updates and news articles related to water quality and environmental health.

h. Reminder Feature: Allows users to set notifications for regular water testing. This is then indicated at the top of the menu screen using a blue dot under the weekly calendar when a reminder is set that falls within the current week.

i. Sidebar Window: Appears after the user reads the welcome screen, providing options to log in/register, access account settings, receive help, and send feedback.

j. Bottom Navigation Bar: This includes (1) settings: allow users to adjust permissions, including enabling GPS location for linking scans to specific locations, (2) notifications: Messages and alerts broadcasts sent to the user's account, (3) weather: Provides users with real-time weather updates and alerts based on their location or selected regions, supporting informed water testing decisions.

The framework of the UI can be visualised using wireframes to design the graphical aspect of the application, as seen in Figure 3.11.

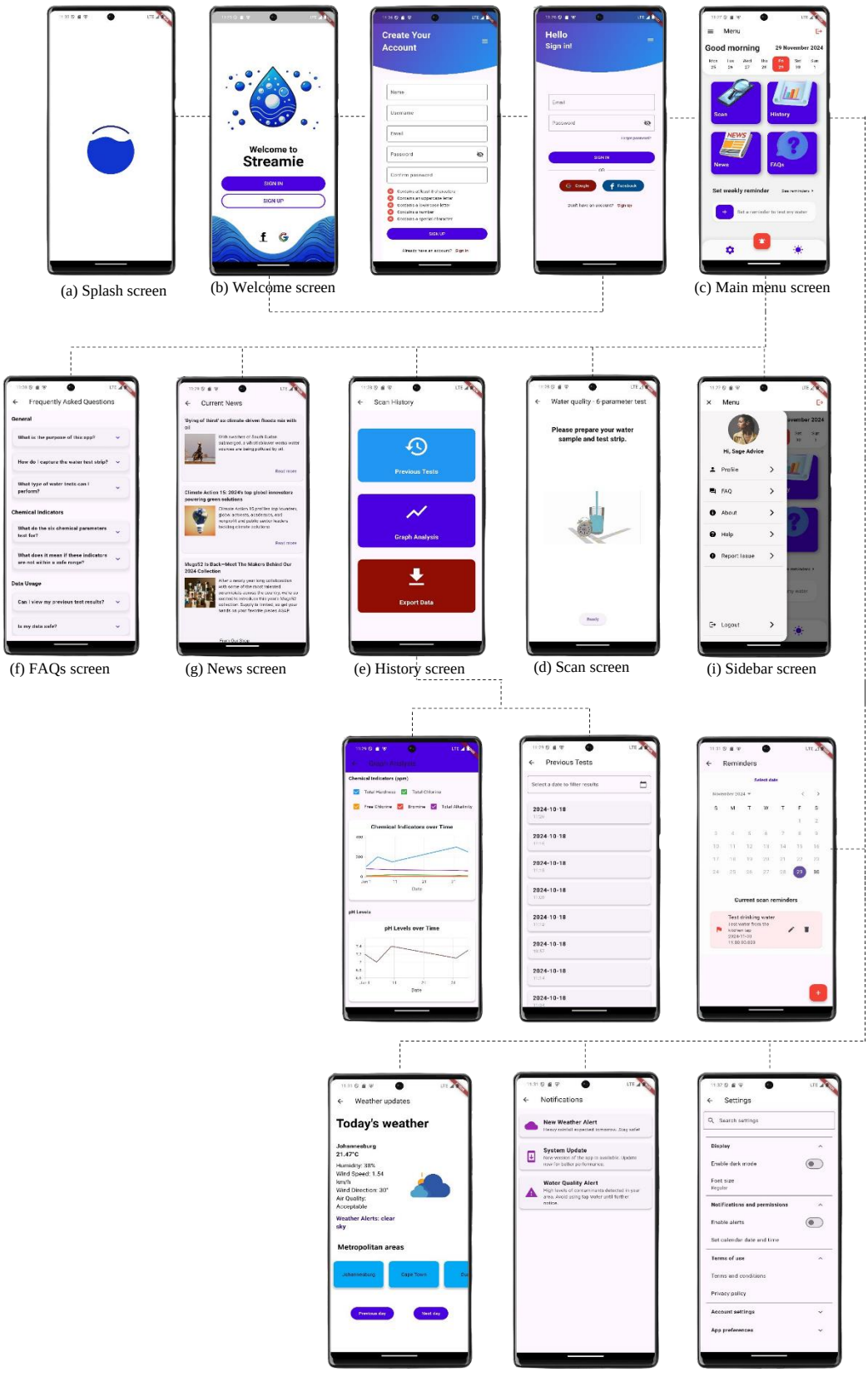


Fig. 3.11 Screens of the app, *Streamie* – from the splash screen to the screens of the bottom navigation

9.2 Development Protocol

The development test protocol outlines the steps from requirement analysis to deployment, ensuring the application meets user needs and functions correctly through design, API integration, testing, bug fixing, and ongoing refinement.

9.2.1 Development Process

This section details the step-by-step development process, from requirement analysis to final deployment, emphasising user-centric design, testing, and iterative refinement.

a. Requirement analysis: An examination of user needs and application objectives forms the foundation of the development process, guiding subsequent design and implementation decisions.

b. UI design: The creation of UI screens and widgets is approached methodically, employing principles of user-centered design to ensure intuitive navigation and optimal user engagement.

c. Application programming interface (API): This refers to the backend development integration points. Backend logic is developed iteratively, focusing on functionalities such as image processing, data storage, and user authentication to provide a seamless user experience. However, the user does not interact directly with the backend. APIs act as intermediaries, allowing communication and data exchange between the frontend and backend components of the application.

d. User permissions: Before user captures an image, they are asked to grant the application permission to capture an image or video using the device's camera. This must be granted for the application to continue, otherwise they are presented with an error. They are also asked to enable their location services – after which they are asked to set their location to 'precise' or 'approximate'. Precise location uses GPS, Wi-Fi, and other sensors to pinpoint exact coordinates, while approximate location relies on broader data like Wi-Fi or cell tower signals to estimate a general area, protecting user privacy and conserving energy

e. Testing: Testing methodologies, including unit testing, integration testing, and user acceptance testing, are employed to validate the functionality and reliability of the application.

f. Bug fixing: Identified issues and bugs are promptly addressed, with iterative refinements made to optimise performance and address user feedback.

g. Deployment: The finalised application is deployed on a mobile platform for further testing, with ongoing monitoring and refinement based on user feedback and usage analytics.

9.3 System Test Procedure

The system test procedure section outlines the methodologies used to ensure the application functions as intended, including unit testing for individual components, integration testing for module

compatibility, user acceptance testing to gather real-user feedback, and performance testing to assess responsiveness and efficiency.

9.3.1 Testing Methods

Unit testing ensures individual components function correctly, integration testing verifies module interoperability, user acceptance testing collects feedback from real users, and performance testing evaluates responsiveness and efficiency.

a. Unit Testing: Individual components of the application undergo thorough testing to ensure they function as intended, with particular emphasis on functional correctness and edge-case scenarios.
b. Integration Testing: The seamless integration of various modules and components is validated through comprehensive integration testing, ensuring interoperability and cohesion across the application.

c. User Acceptance Testing: Real users participate in usability testing sessions to assess the application's usability, functionality, and overall user satisfaction, with feedback informing iterative improvements.

d. Performance Testing: Performance benchmarks are established and evaluated under various conditions to ascertain the application's responsiveness and efficiency, particularly concerning image processing and data retrieval.

9.3.2 Test Cases

To assess the functionality and reliability of the application, various test cases are implemented to ensure key features perform as expected under different conditions.

a. Welcome Screen Test: Verification of the welcome screen's presentation of application details and branding elements.

b. Main Menu Navigation Test: Confirmation of seamless navigation between different sections of the application.

c. Scans Widget Test: Assessment of image capture, upload, and analysis functionalities, including adherence to provided instructions.

d. History Widget Test: Validation of accurate recording and retrieval of past scan data, organised by chronological order.

e. News Widget Test: Verification of user-controlled settings, such as GPS location enablement, and their effect on application behavior.

f. Bottom Navigation Bar Test: Evaluation of broadcast message delivery and user notification mechanisms.

g. Pop-up Window Test: Functional assessment of side window options, including login/registration, account settings, and feedback submission.

h. Error Handling Test: Validation of error handling mechanisms, ensuring appropriate user feedback and system resilience in the face of unexpected events.

By adhering to this structured system design, development protocol, and system test procedure, the mobile application is developed to create access to not only the scan function allowing for the analysis of the test strip but also to allow the user to get updates of the system and for the developing team to receive feedback on how the application is behaving.

10 Database Development

The database is responsible for storing information received from the mobile application through the server, such as user-submitted water quality data, the results of the colourimetric analysis, and GPS coordinates of the image. It then relays this information to the web application while tracking the outcomes of water quality assessments conducted by the application's backend. This section outlines the purpose of the database and the strategies employed.

10.1 Role of Database, Its Structure, and Security

The application integrates with Firestore, a NoSQL database provided by Firebase, to store and process water quality information generated by the system. Firestore is designed to store hierarchical data. It acts as a central repository for managing critical data related to water quality assessment under the *Mapping Water* project created by the developer, including GPS coordinates, user IDs, contaminant levels, timestamps, and safety assessments. By leveraging Firestore's cloud-native capabilities, the application ensures secure, scalable, and real-time data management, which facilitates efficient retrieval and analysis, enabling the potential for a nationwide implementation.

To prioritise user privacy and ensure data integrity, processes are implemented to anonymise and aggregate unsafe water reports. This ensures that the data remains meaningful while protecting individual users' identities. Firebase Authentication is used, which requires users to log in using their registered email and password, Google, or Facebook sign-in methods. Each authenticated user is assigned a unique user identifier (UID), which forms the basis for managing access permissions. Firebase security rules are configured to enforce strict read and write restrictions, ensuring that only users with matching UID values can access or modify their data. For example, rules are set to restrict access to a specific user's data in the `UserGeneratedData` collection.

Validation rules are also applied to confirm that data entries, such as GPS coordinates or water quality information, adhere to expected formats, preventing the injection of malicious inputs. All database communications are encrypted using HTTPS to ensure data security during transmission. Additionally, role-based access control (RBAC) is implemented using Firebase Custom Claims to assign specific permissions based on roles such as admin or user. Firebase's monitoring tools are employed to track and identify any suspicious activities, with alerts configured to notify developers of potential breaches. App Check is enabled to verify that requests to the database originate from the authorised application. Furthermore, API keys are restricted to ensure they are only usable on designated platforms, adding another layer of protection. Data stored in Firebase is encrypted both at rest and in transit, safeguarding sensitive information. These measures collectively ensure that the Firebase database adheres to strict security protocols while maintaining the integrity and privacy of user data. The data collected is also processed in real-time to provide actionable insights. Reports from identical coordinates are analysed to identify unsafe water zones, which are subsequently anonymised for privacy purposes.

10.2 Google Firebase Database Configuration and Management

The Firestore database is configured and continuously managed to ensure optimal performance, scalability, and security for the *Mapping Water* project. Firestore collections and document schemas are structured to support the hierarchical data model required by the application. As Firestore supports indexing and querying of large datasets, it was also chosen because it ensures efficient retrieval of water quality reports even as the database grows.

The application uses Firebase's Blaze plan, a pay-as-you-go model that offers several advantages. This model is particularly cost-efficient, as it charges only for actual usage, making it suitable for applications with variable workloads. The Blaze plan provides scalability by automatically adapting to increased data and user traffic without requiring manual intervention. In addition, Firestore's real-time data synchronisation ensures live updates across all connected clients, eliminating the need for additional server infrastructure, therefore there is a relatively small trade-off between quality and cost, in this regard. Backups and recovery mechanisms are automatically managed by Firestore, reducing administrative overhead. This is particularly important in the decision-making of the database selection due to the developer being the only 'admin' member and the sole developer, and this eliminates additional time that would need to be spent on the management of the system. This brings it full circle to the consideration of the trade-offs between time, cost, and quality of the project, bearing in mind the limited resources and scope of the study.

11 System Integration and Implementation

The integration and implementation of the *Mapping Water* system involve a cohesive approach to merging backend and frontend components with Firebase Firestore. This integration supports the research questions by enabling efficient data collection, storage, analysis, and dissemination of water quality assessments through a scalable and user-centric application.

11.1 Integration, Data Flow, and API Design

The integration of backend code, frontend code, Firebase Firestore, and the web application is integral to the architecture, addressing the research objective of developing a functional and accessible water quality testing system. The backend component is implemented using Flask [154], a lightweight Python framework designed for efficiency and scalability. Flask handles server-side scripting and data processing. The frontend, built with Flutter, interacts with the backend via representational state transfer (RESTful) APIs that provide well-defined endpoints for communication. One endpoint handles HTTP POST requests, for example, when users interact with the frontend interface, such as uploading an image of a water test strip for processing and water quality analysis, while another endpoint allows the application to retrieve the processed results via HTTP GET requests. The backend processes the request, executes all data manipulation steps, and interacts with Firestore to store or retrieve the required data. Once completed, the backend sends a response to the frontend, updating the user interface with the necessary feedback. This architecture collects, processes, and relays water quality data, delivering actionable insights that align with the study's objectives. The data flow is illustrated in Figure 12.

11.2 Experimental Setup

Having described the flow of data, it is important to mention that the experimental system required an additional component to allow beta testers to connect to the application during the testing phase, as the backend code was being hosted on the developer's local computer – acting as a temporary server. Ngrok was used during testing to expose the local backend server to the internet securely. This is a tool that creates a secure tunnel to expose a local server running on a laptop to the internet by generating a temporary public URL that maps to the local server's port, e.g., localhost: 3000 [155]. This URL is then

used in the Flutter mobile application to send the requests to the backend. In the case of the beta testing, it allowed the local backend server, e.g., the Flask server, to be accessible from external mobile devices on the same or a different network. This setup enabled testers to interact with the system in real-time. Therefore, the development computer facilitates code writing, debugging, and simulating the application's behaviour. This coordinated setup supports communication among all major components of the system, as depicted in Figure 3.12. Appendix 3.1 lists the physical components used in the setup.

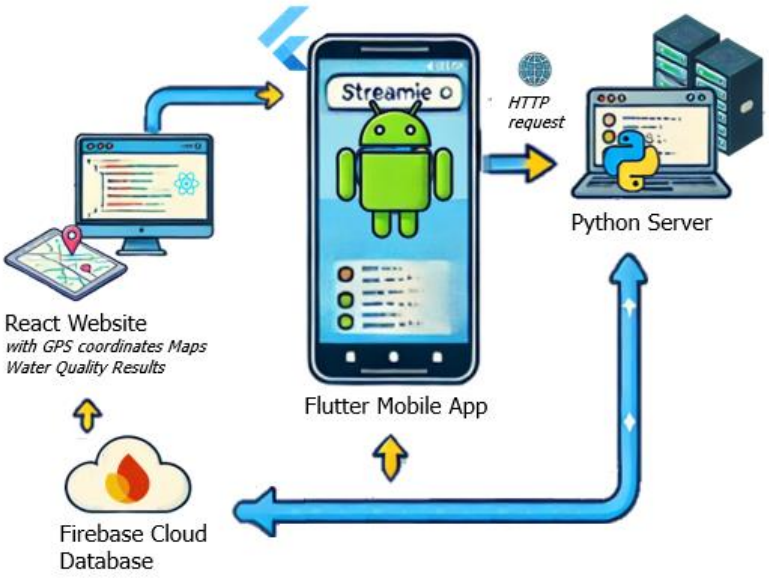


Fig. 3.12 Experimental setup show interaction between key systems of the mobile application

12 System Validation and Testing

System validation and testing for the water quality assessment application employed a comprehensive approach to ensure functionality, reliability, and accuracy across both frontend and backend components. The testing methodology included several distinct methods:

12.1 YOLO-based Testing

To validate the object detection capabilities of the application, YOLO-based testing was conducted. This involved assessing the accuracy and efficiency of the algorithm in detecting and classifying objects, such as water test strips, under various conditions and environments. This testing evaluated the model's performance in real-time scenarios, considering factors such as lighting conditions, angles, and strip orientations.

12.2 Colour Detection Testing

A series of tests were conducted to evaluate the accuracy and consistency of colour detection algorithms used in the application. Different water test strips with varying physical conditions, such as moisture levels, degradation, and lighting variations, were employed to simulate real-world scenarios. This testing process involved comparing the detected colours against predefined colour ranges to ensure precise assessment and classification of water quality parameters.

12.3 Integration Testing

Integration testing was performed to validate the interaction between the frontend UI, backend logic, and database functionality. This testing phase focused on verifying data flow, API endpoints, and communication protocols to ensure smooth operation and data integrity throughout the application.

12.4 User Acceptance Testing

User acceptance testing was conducted to assess the application's usability, intuitiveness, and overall user experience. Real users interacted with the application to provide feedback on its functionality, interface design, and feature usability. User Acceptance Testing (UAT) helped identify any usability issues, or information not being relayed correctly, timely or at all between system components. It thereby highlighted areas for improvement, enabling iterative refinement based on user feedback.

12.5 Continuous Monitoring and Iteration

Throughout the testing process and beyond, continuous monitoring and iteration were essential aspects of system validation. Performance metrics, user feedback, and bug reports were monitored closely to identify areas for optimisation and enhancement. Regular updates and iterations were rolled out based on these insights to improve the application's functionality and address any issues or concerns raised during testing. By employing a testing strategy encompassing YOLO-based testing, colour detection testing for both the RGB and HSV colour spaces with varied strips, integration testing, and user acceptance testing, the water quality assessment application underwent thorough validation to ensure its reliability, accuracy, and user satisfaction within the refines of the scope of the project. Additionally, continuous monitoring and iteration based on beta testers feedback and performance metrics were integral to refining and enhancing the application throughout its lifecycle, ensuring its effectiveness and usability in real-world scenarios.

13 Limitations of Methodology

13.1 Limitations of the Methodological Approach and Implementation

While the methodology and design discussed present a comprehensive approach to water quality monitoring and safety assessment, several limitations warrant consideration:

13.2 Reliance on Colour Classification Accuracy

The accuracy of water quality assessment heavily depends on the precision of the colour classification algorithm. Any inaccuracies or variations in colour detection could lead to erroneous safety determinations, potentially compromising public health.

13.3 Sensitivity to Environmental Factors

The efficacy of the GPS-based monitoring system may be influenced by environmental factors such as weather conditions, terrain features, and signal interference. In remote or rugged areas, obtaining precise GPS coordinates could prove challenging, impacting the reliability of location-based safety assessments.

13.4 YOLOv8 Model Limitations and Considerations

While YOLOv8 offers impressive performance, it may encounter challenges in detecting objects under extreme conditions or in complex environments. Model limitations include occasional misclassifications and difficulties in handling occlusions or cluttered backgrounds.

13.5 User-dependent Data Acquisition

The quality of data captured through the mobile application is contingent upon user compliance and adherence to testing protocols and instructions provided by the application. Inconsistent or erroneous data input by users may introduce biases or inaccuracies, undermining the reliability of safety assessments.

13.6 Limited Scope of Chemical Indicators

The reliance on a predefined set of chemical indicators may overlook emerging contaminants or localised pollutants not accounted for in the monitoring framework. This system only assesses six chemical indicators, which include two different forms of chlorine. These indicators do not provide a wide enough view of a potentially harmful water profile to produce a more advanced analysis. As water quality concerns evolve, the static nature of the indicator set may restrict the system's adaptability and relevance. Chemical indicators in the test strip such as total alkalinity do not show an unsafe upper limit that can be detected on the test strip. 360 is not unsafe for an upper total alkalinity range. Similarly, the lowest value for pH i.e., 6.0. is not an unsafe level for pH – to reach an unsafe level the strip would need to be able to indicate a pH level below 6.0. Therefore, the strip is limited in giving accurate unsafe ranges, and in some cases can only warn the user as they approach unsafe limits.

13.7 Privacy and Security Concerns

Despite efforts to anonymise GPS coordinates in the database, and allow the user to set their GPS coordinates to ‘precise’ or ‘approximate’ when capturing their test strip image, there remains a risk of unintended data exposure or privacy breaches. Adequate safeguards must be implemented to mitigate the potential misuse or unauthorised access to sensitive user information.

13.8 Scalability Challenges

As the monitoring network expands to encompass larger geographical areas or accommodate a growing user base, scalability issues may arise in data management, processing, and transfer. Ensuring scalability requires well-developed infrastructure and resource allocation.

13.9 Interpretation of Safety Thresholds

The determination of safety thresholds for chemical indicators, based on regulatory standards such as SANS241, necessitates periodic review and validation to account for evolving scientific understanding and health guidelines. Failure to update safety thresholds promptly could lead to misinterpretation of safety statuses and inadequate risk mitigation measures.

13.10 Resource Intensive Maintenance

Maintaining and updating the software infrastructure, including the database, algorithms, and mobile application, demands ongoing resources in terms of personnel, time, and funding. Without sustained support, the system's effectiveness and reliability may diminish over time. Addressing these limitations

requires a multifaceted approach encompassing continuous technological innovation, stakeholder engagement, regulatory oversight, and community participation. By actively addressing these challenges, the water quality monitoring system can evolve into a more adaptive, and inclusive framework for safeguarding public health and environmental sustainability.

14 Ethical Considerations

14.1 Data Privacy and Security

The project will involve the use of personal data. Therefore, the application implements stringent measures to safeguard user data, including personally identifiable information (PII), collected during the registration and testing phases. Strict privacy protocols are in place to ensure the protection of user data, with data encryption, secure storage, and stringent access controls being integral components.

It is important to restrict the information that will be used for mapping and to filter the data that will be stored in the database. Once the user submits their test strip for analysis, the user profile information associated with the uploaded sample is excluded so as to avoid any personal details such as the owner's name, cell phone number, email address, and any identifying information related to social media or other smart applications are made public. This is achieved by assigning the user a generic user ID once the database receives their information to ensure their information cannot be traced.

14.2 Informed Consent

Informed consent was obtained from all users during the data collection process as they were informed by the WaterCAN team that their water test strip images would be used to evaluate South Africa's water quality. In addition to this, beta testers of the application are also required to give informed consent before testing the application and providing feedback on its functionality. This is in line with the Wits ethics requirements. Users can submit images of their water tests for analysis, they must also give informed consent by reading and ticking an agreement made available on the application. Users are provided with clear and concise explanations regarding the types of data collected, ensuring transparency and voluntary participation in research activities.

14.3 Algorithmic Transparency and Accountability

Transparency will be prioritised by maintaining a comprehensive privacy policy and the provision of accessible information on data usage. The project prioritises transparency in the functioning of the machine learning model, providing users with insights into how decisions are made and the implications of model predictions. Mechanisms for ensuring accountability and providing recourse for users affected by erroneous or biased predictions must also be established in an agreement that the user must acknowledge to use of the application: a legal professional must be consulted concerning this.

14.4 User Safety and Well-being

User safety and well-being are paramount considerations, with safeguards implemented to limit misuse or harm resulting from application usage. Accurate and contextually relevant information is provided to users to empower them to make informed decisions about their water quality. Users will also be encouraged to remain informed on water-related matters disseminated by trusted water regulatory sources.

14.5 Bias and Fairness

Efforts are made to mitigate biases in the dataset used for training the machine learning model, ensuring fairness in model predictions across diverse user populations. Techniques such as data anonymisation and bias detection are employed to minimise potential biases and ensure equitable outcomes.

14.6 Accessibility and Inclusivity

The application is designed to be accessible to users with a smartphone with average camera quality, as set by the market, and internet access. Although this may exclude those without mobile devices, the application allows for the creation of more than one user profile on the same device, to potentially allow for the sharing of devices whilst still using separate accounts. A potential future application is to make the application accessible to users who may need a voice assistant. The application is currently available in English, a widely spoken language in the country and the current lingua franca [156].

14.7 Ethical Use of Technology

Ethical responsibilities of the developer in designing and deploying technology are upheld, aligning with principles of beneficence, non-maleficence, and respect for autonomy. Ethical dilemmas encountered during the project are addressed in accordance with ethical guidelines and regulations that must be established prior to deployment, ensuring ethical use of technology for societal benefit.

In addition, in order to capture and scan the water test strips, users will be asked to enable their camera for the picture. The camera will be disabled again after the image has been taken. Users will be able to control the settings that give the application access to their camera in their application settings. The application will also request that they enable their location settings to find their location. The settings tab will allow users control over when and how they give permission to the enabling of these technological features.

14.8 Social Impact and Stakeholder Engagement

The project acknowledges the broader social implications of deploying the application, including its potential effects on public health and environmental awareness. Perspectives of stakeholders, including end-users, healthcare professionals, and advocacy groups such as OUTA, are considered in shaping the application's development and potential deployment.

15 Conclusion

The development of a water assessment application demands meticulous attention to methodological rigour, ensuring the reliability, accuracy, and ethical integrity of the system. Throughout this chapter, various facets of the methodology employed in creating such an application have been explored, ranging from software integration to ethical considerations. This conclusion synthesises the key insights gleaned from each section, highlighting the importance of methodological consistency in achieving the overarching objectives of the study.

The methodology outlined herein underscores the significance of adopting a comprehensive approach to water quality monitoring. By integrating advanced technologies such as machine learning algorithms, GPS-based systems, and image processing techniques, the application aims to provide users with real-time assessments of water safety. The use of methodologies such as YOLO-based object detection and colour classification algorithms enhances the application's ability to detect and classify contaminants accurately, thereby bolstering public health efforts.

There are ethical considerations that need to be considered woven through the entire methodology, reflecting a commitment to safeguarding user privacy and ensuring responsible technology use. Measures such as data anonymisation, informed consent protocols, and stringent privacy policies underscore the ethical imperative inherent in the project. By prioritising user safety, data security, and algorithmic transparency, the application seeks to engender trust and confidence among its user base.

Despite the attention to detail paid to the methodological approach, the study is not without its challenges and limitations. Factors such as reliance on colour classification accuracy, sensitivity to environmental variables, and scalability concerns pose significant hurdles to be addressed. However, by acknowledging these limitations and adopting a proactive stance towards addressing them, the project endeavours to continuously enhance its efficacy and relevance.

Looking ahead, the methodology chapter sets the stage for future research endeavours and technological innovations in the field of water assessment. The application's potential for scalability, adaptability, and inclusivity opens doors to a myriad of possibilities for advancing public health initiatives and environmental sustainability efforts through already existing and prominent devices such as smartphones. Moreover, the ethical framework established herein serves as a guide for future studies, emphasising the importance of responsible technology deployment and stakeholder engagement.

Chapter 4: Experimental Results

1 Introduction

This chapter presents the results and findings of the water monitoring system developed during this research. It focuses on the technical performance of the backend code, which manages the processing and analysis of the images. This includes how the mobile application interacts with the Firebase database and web application and how these interactions contribute to effective water quality monitoring. Specifically, the results provide insights into the system's core functionalities' accuracy, speed, and reliability.

A detailed analysis of the results obtained from key image processing techniques, including brightness correction, glare detection, and white balance adjustments, is discussed. Furthermore, the paper explores the implementation of the YOLOv8 model for the precise detection of chemical patches on water test strips. Lastly, it evaluates the colour classification code's ability to classify the colour patches of each parameter and their role in the final water quality prediction algorithm.

2 Mobile Application Server-side Code Performance

The backend code of the mobile application is responsible for handling the image processing of the water test strips, object detection using deep learning models, and colour classification to identify chemical indicators. This section evaluates the backend functionalities' performance, focusing on improving the system's accuracy and efficiency.

2.1 Image Processing Overview

The results of the three primary operations are presented to give insight into the functionality of the pre-processing of the user-uploaded images, through metadata extraction**,** colour correction and brightness adjustment, and glare detection and removal.

2.1.1 Metadata Extraction

The following section presents the quantitative results of the metadata extraction process, specifically focusing on the successful retrieval of EXIF data, including GPS location, from a sample set of images captured on various mobile devices.

2.1.1.1 Quantitative Results of Metadata Extraction

In this study, the term "metadata" is used to describe the extraction of EXIF data, as EXIF is a specific subset of metadata embedded within image files, providing essential information such as GPS location, timestamp, and camera settings. The metadata extraction function written by the developer, `extract_metadata_from_image()`, was tested on a sample set of 100 images captured on both Android and Apple mobile devices at different locations. As seen in Table 1, out of the total number of images, only 85% of the images had their location enabled on the device at the time that the images were captured. However, metadata – whether GPS coordinates were included or not – was extracted from 90% of the images, with information about the image and mobile device being provided. Even though 85 out of the 100 images had GPS data available for extraction, GPS coordinates were extracted from 83 images, resulting in a 97.7% success rate at extracting GPS coordinates from images that had the information available.

Table 4.1 Metadata extraction results

Extraction Metric	**Value**
Images with metadata extracted	90
Images with location function enabled	85
Number of successful GPS data extractions	83
Total number of images	**100**

The results in Table 4.1 demonstrate the reliability of the function but also reveal that there is room for improvement in the function's ability to extract GPS data from all images that have their location, whether this was an exact or an approximate location that was provided at the time that the image was capture. The metadata extraction function does not appear to be able to extract GPS data from all devices or in all formats in which this data may be made available or stored on different mobile devices. The code can be improved to recognise and adapt to these different formats.

2.1.2 Colour Correction and Brightness Adjustment

The brightness adjustment step aims to standardise the brightness levels of images, while white balance correction compensates for colour biases caused by lighting conditions.

2.1.2.1 Brightness Adjustment Results

The `adjust_brightness()` function was tested on 50 images, normalising their brightness to a target value of 0.5. The improved brightness levels were expected to enhance the visibility of chemical patches, which are required for subsequent object detection and colour classification. This adjustment was evaluated by comparing the mean brightness values of the original images against the adjusted images. Figure 4.1 shows a selected sample of images showing the visible differences achieved through brightness adjustment. The enhanced images exhibit a clearer delineation of chemical patches, making them more distinguishable for subsequent analysis. This improvement in the visibility of the test strip is anticipated to contribute positively to detection accuracy.



(a) (b)

Fig. 4.1(a) illustrates the original images in the sample that were deliberately taken in darker lighting conditions, and (b) shows the effect of the brightness adjustment code applied to the original images

2.1.2.2 Visual Validation of the Results of White Balance Processing

The `perform_white_balance` () function, aimed at correcting colour biases in images using the Gray World Assumption [149], was tested on a sample of 50 images with various lighting conditions. Figure 4.2 presents a side-by-side comparison of original and colour-corrected images. The original 50 images exhibited significant colour casts due to improper lighting conditions. Figure 2 shows the outcome of a sample of 16 images before and after being passed through the white balance function and demonstrates the reduction of colour casts and enhancement of the clarity of chemical, with all images moving closer to the target values.

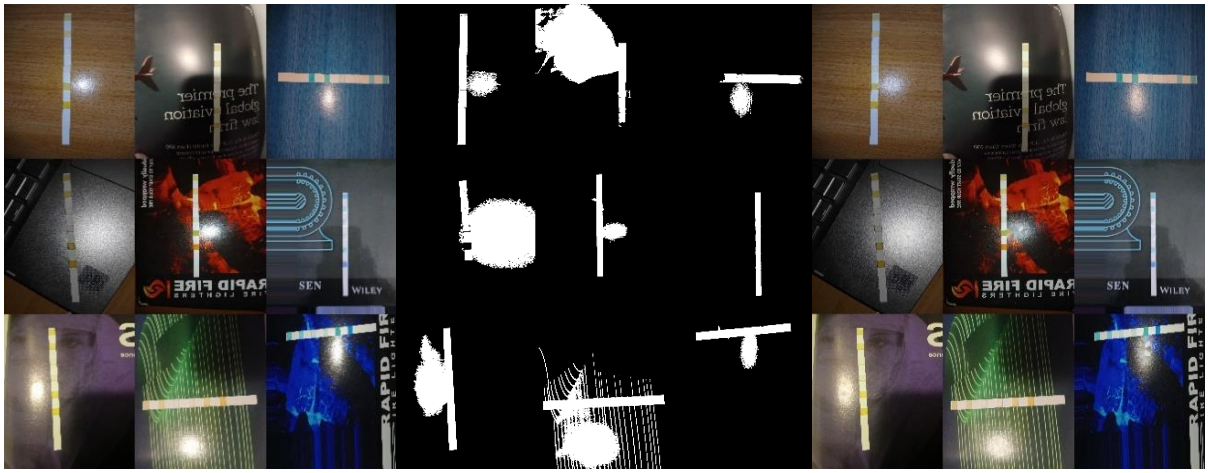


(a) (b)

Fig. 4.2 (a) demonstrates the original images selected from the set of 50 images before white balancing was performed, and (b) shows the outcomes of the colour correction

2.1.3 Glare Detection and Removal Results

As glare from lighting sources can obscure important features in the test strip images, the glare detection and removal functions, namely `detect_glare()` and `remove_glare()`, were developed and implemented over a period of two months to ensure the improvement in the visibility of chemical patches, ensuring that pixels in the colour patches were not replaced with white pixels, thereby interfering with the colour classification process, and resulting in erroneous water safety predictions. To evaluate the effectiveness of the glare detection function, a test was conducted on a sample of images known to contain glare artefacts. The primary objective was to assess the function's capability to accurately identify the presence of glare and the specific regions affected within each image. If these glare regions intersected with the ROIs on the test strips, the glare had to be auto-filled by replacing the pixels affected by the glare with the colour of the neighbouring pixels. The functions were tested with over 200 images to finetune them. Once this was accomplished, a set of 100 images was intentionally captured with glare. The glare functions successfully identified glare in 96% of the tested images and auto-filled the affected ROIs. Figure 4.3 illustrates the outcome of the glare detection process.



(a) (b) (c)

Fig. 4.3 (a) shows a sample of images taken from the original 100 images with glare, (b) the glare mask where glare has been detected and (c) the reduction of the glare where it obscures the view of any of the six patches

2.2 Results of Object Detection Using YOLOv8 Nano Model

The effectiveness of the YOLOv8 model detection is assessed through quantitative and qualitative evaluations, with a focus on precision, recall, mAP for accuracy and training and validation losses.

2.2.1 Training and Validation Losses, and Evaluation Metrics Interpretation

The dataset contained 7000 strip images, with an 80/20 ratio for training and validation respectively, as described in Chapter 3.

2.2.1.1 Training and Validation Loss Metrics

During training, the training loss and validation loss were monitored over 50 epochs. Figure 4.4, shows loss curves for both training and validation and precision and recall metrics.

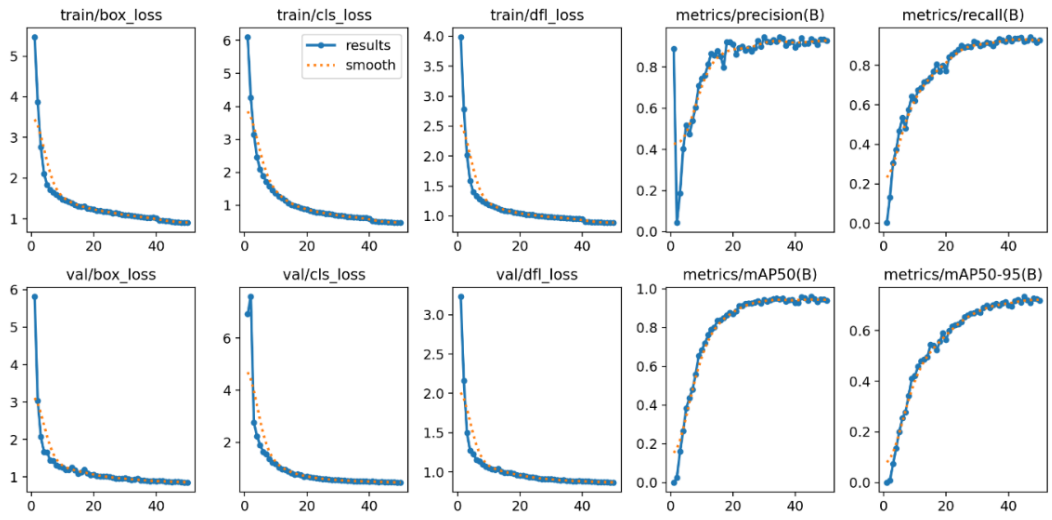


Fig. 4.4 Training and validation metrics and losses over 50 epochs

The dataset consisted of 7000 test strip images, divided into an 80/20 ratio for training and validation, as specified in the methodology. The training and validation losses were tracked over 50 epochs to monitor the model's learning progress and minimise the risk of overfitting. Figure 4 presents the loss curves for training and validation, alongside metrics for precision, recall, and mAP, used to answer the research questions.

The training losses comprise three components: box loss, class loss, and distribution focal loss (DFL). The *train/box_loss* metric evaluates the accuracy of bounding box predictions, showing a steady decrease and stabilisation around epoch 30, which reflects improved localisation precision. Similarly, *train/class_loss*, which measures the model's ability to correctly classify objects, follows a similar trend, indicating progressive gains in classification accuracy. The *train/dfl* metric, which assesses fine-grained localisation, also decreases over time, demonstrating the model's ability to refine object boundaries throughout training. Validation losses, such as *val/box_loss*, *val/class_loss*, and *val/dfl_loss*, exhibit trends consistent with their training counterparts. The reduction and stabilisation of these validation losses confirm the model's ability to generalise effectively to unseen data while avoiding overfitting.

Metrics like precision, recall, and mAP provide an assessment of detection performance. The *metrics/precision(B)* curve stabilises above 0.9, reflecting the model's ability to minimise false positives. Recall, which measures the proportion of correctly detected objects, improves steadily, signifying a reduction in false negatives. The *metrics/mAP50(B)*, representing mAP at a 50% IoU threshold, stabilises at around 0.95, showcasing adequate detection performance for this study's purpose. However, the stricter *metrics/mAP50-95(B)*, which evaluates mAP across a range of IoU thresholds, stabilises at approximately 0.7, indicating good but slightly reduced performance under more demanding conditions.

In this process, early stopping was excluded to allow the model to complete all 50 epochs, ensuring full optimisation of parameters for both classification and localisation. Although early stopping could have shortened training time, its omission allowed the model to converge fully, leading to consistent and stable performance across metrics [157]. Additionally, data augmentation techniques, such as flipping, scaling, and random cropping, were implemented to enhance the model's ability to generalise better. As described in Chapter 3. These methods introduced variability into the dataset, improving the model's adaptability to different object orientations, sizes, and placements. This contributed to notable improvements in precision, recall, and overall generalisation. These results are consistent with previous findings that suggest YOLOv8's improved architecture leads to faster and more stable convergence [115].

2.2.1.2 Confusion Matrix and PR Curve Interpretation

The normalised confusion matrix in Figure 4.5 shows the proportions of correctly and incorrectly predicted labels for each class. The high accuracy achieved across the key water testing parameters is noteworthy. For instance, the model achieved 98% accuracy in detecting test strips in their correct orientation, and similarly high results were observed for total hardness, total chlorine, bromine, and pH, with accuracies ranging from 95% to 98%. This suggests that the model is effective in identifying these core chemical parameters, essential for water quality assessment.

However, some challenges were noted with specific classes. While the detection of free chlorine is relatively high with 94% accuracy, there are small misclassifications where free chlorine is confused with total hardness, total chlorine, and bromine. Additionally, the model struggles more with detecting rotated test strips, achieving 75% accuracy. The confusion primarily arises between the rotated strip and the background, indicating that the model has difficulty distinguishing between rotated strips and non-object areas, which could affect overall accuracy in certain scenarios.

Another point of concern is the misclassification of the background, where 1-4% of objects such as total hardness, total chlorine, and free chlorine are incorrectly identified as background. This suggests that further refinement could help the model better distinguish objects from non-object areas. With some optimisation in these aspects, the model could potentially achieve even higher accuracy and reliability. That said, the performance of the model is satisfactory as it meets the minimum accuracy benchmark of 80% under both ideal and non-ideal conditions for proof-of-concept, as set out by the sub-research question. This translates to negligible errors in object detection and therefore classification of classes in the overall algorithm.

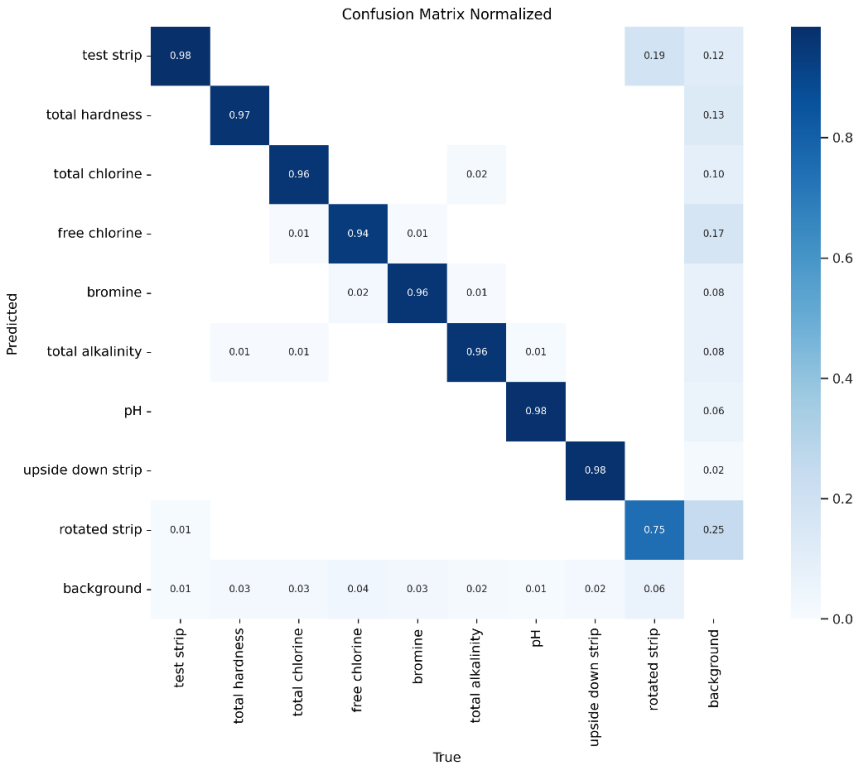


Fig. 4.5 Confusion matrix for custom-trained YOLOv8 nano model

The metrics in Table 4.2 were calculated based on the bounding boxes predicted by the model, compared with the ground truth annotations for each class. The results are based on the last instance of training and not the best-performing like the confusion matrix, reflecting precision, recall, F1-score, and mAP@0.5 metrics for each class.

Table 4.2 YOLOv8 Object Detection Performance

Class	Description	Precision (%)	Recall (%)	F1-Score	mAP@0.5 (%)
Class 0	Correct Orientation	94.8	95.3	95.0	95.2
Class 1	Total Hardness	90.1	89.8	89.9	90.0
Class 2	Total Chlorine	88.3	87.5	87.9	88.0
Class 3	Free Chlorine	86.8	86.1	86.4	86.6
Class 4	Bromine	91.2	90.9	91.0	91.1
Class 5	Total Alkalinity	89.4	89.0	89.2	89.3
Class 6	pH	92.0	91.5	91.8	91.9
Class 7	Rotated Test Strip	74.1	73.6	73.9	74.0
Class 8	Upside-down Test Strip	70.5	69.9	70.2	70.4

As seen from Table 4.2, the model performed well in identifying both the correct orientation of the test strip (class 0) and the chemical patches (classes 1–6), reinforcing findings from previous research that advocate for the use of advanced deep learning techniques in environmental monitoring [158]. The performance dropped for incorrectly oriented test strips (classes 7 and 8), but this was expected due to the relatively smaller number of such examples in the dataset.

Additionally, a precision-recall (PR) curve was generated to visualise the trade-off between precision and recall at various confidence levels, as seen in Figure 4.6.

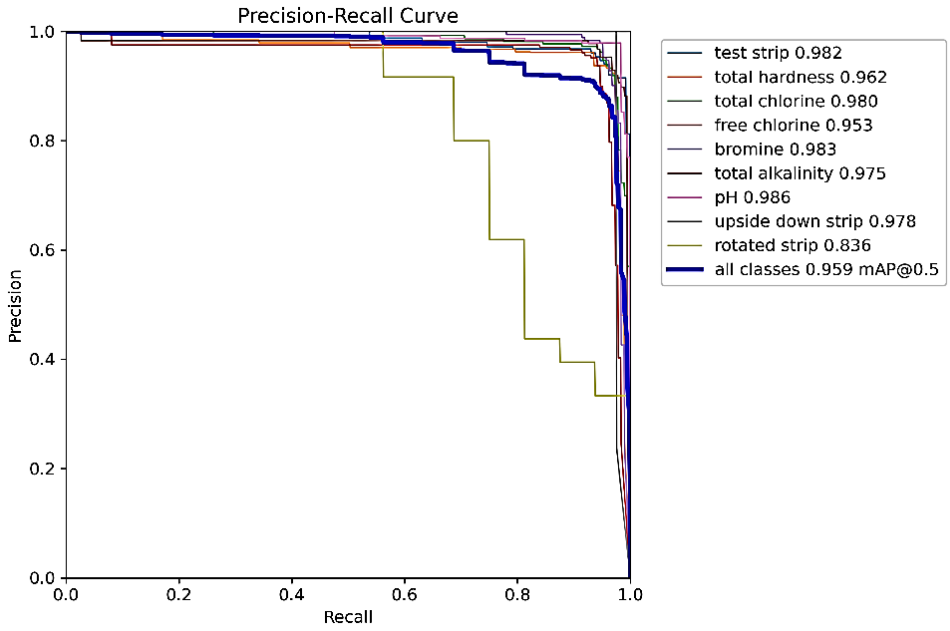


Fig. 4.6 Precision-recall curve for custom-trained YOLOv8n model

The overall performance of the model is reflected in the mAP@0.5, which stands at a value of 0.959, meaning that the model successfully detected objects with at least 50% overlap between the predicted and ground truth bounding boxes in 95.9% of the cases. This high score indicates that, on average, the model demonstrates excellent accuracy across all classes at an IoU threshold of 0.5. For key classes such as test strips (0.982), total chlorine (0.980), bromine (0.983), pH (0.986), and total alkalinity (0.975), both precision and recall values are exceptionally high. This suggests that the model consistently identifies these objects with minimal false positives and negatives. Although free chlorine exhibits slightly lower precision and recall at 0.953, it still performs acceptably. Notably, the upside-down strip shows a relatively strong performance as well, reinforcing the model's capability to detect diverse classes accurately.

In contrast, the rotated strip class is where the model performs least reliably, achieving the lowest precision-recall score of 0.836. This aligns with findings from the confusion matrix, which indicated difficulties in accurately identifying rotated strips. The shape of the PR curve for most classes approaches the ideal top right corner, signifying high precision even at elevated recall levels. However, the curve for rotated strips deviates significantly from this ideal, indicating that the model struggles to maintain a balance between precision and recall for this class, suggesting the need for additional training or tuning in future if the developer wishes for better performance before potential deployment.

One should note that these results are being interpreted and used as predictions of future performance, as one of the assumptions is that the user will use the application as intended, following instructions provided on the application and elsewhere.

2.2.2 Bounding Box Accuracy and Visualisation

Figure 4.7 shows that the model effectively localised chemical patches on test strips, as shown by the closely aligned bounding boxes in ideal conditions. In non-ideal conditions, while slight misalignments occurred, the model still demonstrated reliable detection capabilities.



(a) (b)

Fig. 4.7 (a) shows the validation label images and (b) shows the validation prediction images

The validation label images contain the ground truth annotations, while the validation prediction images display the model's predictions after running the validation data through the YOLOv8 model. What highlights the model's performance is that it can still predict the bounding boxes in the validation set without any ground annotation being provided, as seen in image 2102 in Figure 4.7(b). Similarly in image 1113 (number shown in white text in the top left-hand corner of all images, e.g. 1093.png), both test strips are detected and labelled in Figure 4.7(b), even though only one of the strips were labelled for training in Figure 4.7(a).

2.2.3 Inference Speed and Latency Analysis

For real-time object detection, the inference speed of the YOLOv8n model is a critical performance measure. The average inference time for each image was approximately 100ms, allowing the system to process 10 frames per second. This was measured on the same GPU cluster node. A breakdown of the model's latency is shown in Table 4.3.

Table 4.3 Latency Breakdown for Model Inference

Component	Average Time (ms)
Loading Time	50
Pre-processing Time	30
Inference Time	100
Post-processing Time	20
Total Latency	**200**

The overall latency of 200ms ensures that users receive near-instant feedback, making the system suitable for mobile applications.

2.2.4 Comparison to Expected Results

To assess the model's performance, various factors were considered, including its ability to detect chemical patches under different conditions and environments. Ground truth annotations were used to compare the model's predictions. As expected, based on the results observed so far from the YOLO model, in most cases, the model accurately detected the chemical patches, but there were a few discrepancies. In ideal conditions, the model's performance closely matched the expected results, with minor errors in bounding box placement. Under non-ideal conditions, the model missed lightly coloured patches occasionally, such as total chlorine and the lower ranges of bromine patches, due to the cluttered backgrounds. The model was trained on images captured in controlled environments but tested on images from different real-world settings. Despite this difference, the YOLOv8n model generalised reasonably well, maintaining high detection accuracy for patches in unfamiliar environments. Several edge cases were identified during testing. For instance, the model's confidence scores dropped when images were poorly lit. When patches were partially covered by other objects, the model struggled to detect them correctly, leading to false negatives. Lower-resolution or blurry images affected the model's ability to correctly detect and classify chemical patches. In these cases, the model's precision decreased by 10-15% which is in line with [115].

2.2.5 Unit Testing for the Object Detection Module

2.2.5.1 Test Cases for Object Detection

The following unit test cases were defined to evaluate the performance of the object detection module across different conditions:

i. Correct Orientation: Ensure the model accurately detects a correctly oriented test strip.
ii. Low Lighting: Test the detection capability under low-light conditions.
iii. High Resolution: Validate the model's accuracy on high-resolution images.
iv. Blurred Image: Test detection performance on blurred or low-quality images.

These test cases include real-world variations in lighting and image quality that are likely to occur in practical usage scenarios. Unit tests were written using the PyTest framework, and specific functions within the object detection module (e.g., `detect_strip`, `detect_patches`, `label_patches`) were tested individually.

2.2.5.2 Unit Test Results

The results of the unit tests for the object detection module are summarised in Table 4. Each test case was executed multiple times to ensure consistency. Both expected and actual outcomes were recorded.

Table 4.4 Object Detection Unit Test Results

Test Case	Function	Description	Expected Outcome	Actual Outcome	Status
TC1: Correct Orientation	`detect_strip`	Correctly oriented strip	Accurate detection	Accurate detection	Pass
TC2: Low Lighting	`detect_strip`	Strip in low lighting	Slightly lower accuracy	Slightly lower accuracy	Pass
TC3: High Resolution	`detect_patches`	High-resolution image	Accurate detection	Accurate detection	Pass
TC4: Blurred Image	`detect_patches`	Blurred image	Detection may fail	Detection failed	Pass
TC5: Correct Labelling	`label_patches`	Correct labelling of patches	Accurate labelling	Accurate labelling	Pass

The analysis of unit test results showed that the model successfully detected the correct orientation of the test strip in all cases, passing TC1. While detection accuracy decreased under low-light conditions (TC2), it maintained reasonable accuracy. The model excelled with high-resolution images (TC3), but detection failures occurred with blurred images (TC4), highlighting the importance of clear inputs.

2.3 Colour Classification for Water Test Strips Using Computer Vision

This section analyses the results obtained from the colour classification process, and discusses the impact of RGB to HSV conversion on accuracy.

2.3.1 Colour Classification and Chemical Parameter Detection

Before evaluating the results of the colour classification, the safe ranges for each chemical parameter – according to the SANS241 for drinking water – must be clearly stated. Table 5 gives the ranges of the chemical indicators along with the SANS241 safety parameters.

Table 4.5 Chemical Concentration Limits and Detected Ranges

Chemical Indicator	Detected Range (ppm)	SANS 241 Unsafe range (ppm)
Total Hardness	0-425	> 120
Total Chlorine	0-20	> 5
Free Chlorine	0-20	> 3
Bromine	0-40	> 1
Total Alkalinity	0-360	> 360*
pH	6.0-9.0	< *6.4 and > 8.2

*This upper range of the chemical indicator's maximum for alkalinity and lower range for pH only approaches the unsafe values but does not reach unsafe levels. Therefore, the test strip cannot identify unsafe levels for the water sample in these two regards.

2.3.2 Pre-set HSV Ranges and Colour Classification Accuracy

Converting RGB to HSV introduces challenges due to slight discrepancies between manually set HSV ranges and those detected from new images, leading to classification errors under non-ideal conditions. Differences of 1.7% to 2.5% in HSV values, caused by factors like lighting and pixel selection, can particularly affect similar colours, such as free chlorine and bromine. Automating the HSV range determination process could improve classification accuracy by reducing human error.

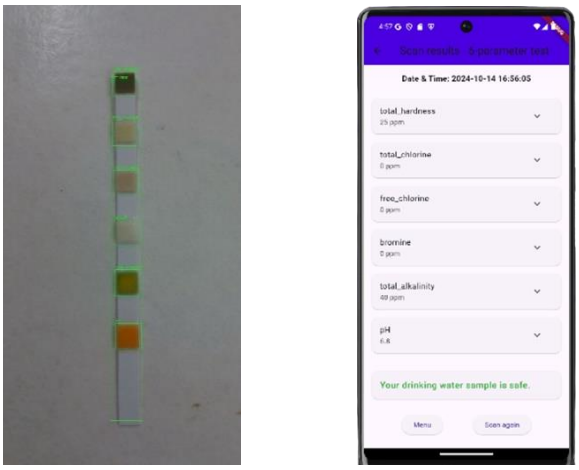
2.3.3 Evaluation of Results for Colour Classification Experiment

To assess the accuracy of the colour classification algorithm, test strip images exposed to standard solutions were captured under various conditions processed through the mobile application and captured at different stages for comparison with lab-based readings.

2.3.3.1 Inference of Colour Classification on Unseen Images Post Object Detection

To evaluate the performance of the colour classification algorithm, a laboratory experiment was conducted on a set of 120 images. A subset of 82 test strip images were selected and will be used to demonstrate the results of the strips being exposed to standard solutions under varying conditions. These standard solutions were created in the laboratory and their chemical concentrations were confirmed using third-party laboratory equipment and formally recorded. Appendix 4.1 details the protocol followed in the laboratory when conducting this experiment. Images of the test strips, after being exposed to each solution were captured under both ideal – controlled lighting, clean backgrounds, high resolution – and non-ideal – poor lighting, cluttered backgrounds, lower resolution – conditions, simulating real-world usage of the monitoring system.

These images were passed through the mobile application and the results of the test strip were recorded, and compared to the readings of the third-party laboratory equipment, as well as manual readings captured of each strip. These unseen images were also run independently through the YOLOv8n model to confirm that the ROIs in the strips were accurately detected. The results of the laboratory equipment, manual readings and the analysis provided by the app are all recorded in Appendix 4.2. The algorithm achieved an overall accuracy of 91.46%, which is significantly higher than the projected accuracy of 70% observed in unprocessed images that do not make use of AI-based object detection [159]. Figure 4.8 shows an example of the test strip that was passed through both the mobile app and the object detector to confirm all ROIs were detected. It also shows a screenshot of the results obtained by the mobile app next to the test strip.



(a) (b)

Fig. 4.8 (a) shows the test strip after object detection, with (b) a screenshot of the results for the same strip from the mobile application

2.3.4 System Performance: Water Safety Classification

These 82 images from the laboratory experiment were also used to determine whether the tested water samples were safe for consumption. This was done according to the SANS 241 drinking water

standards, which are part of the results provided by the water quality application. The results can be seen in Figure 8. The test images included varying chemical compositions, some falling within the acceptable safety ranges and others exceeding the thresholds for safe drinking water. Table 4.6 below summarises the system's overall performance in accurately determining the safety of the water samples.

Table 4.6 Average Water Safety Classification Accuracy

Outcome	**Number of images**	**Percentage of total 82 images (%)**
Safe Samples Correctly Classified as Safe	54*	65.85%
Unsafe Samples Correctly Classified as Unsafe	26**	31.71%
Unsafe Samples Incorrectly Classified as Safe	2	2.44%
Safe Samples Incorrectly Classified as Unsafe	0	0%

*Eight of the images correctly classified as safe were incorrectly identified (as the wrong range) but the range it was misidentified as being was still safe.
**One of the images correctly classified as unsafe was incorrectly identified (as the wrong range) but the range it was misidentified as being was still unsafe.

As shown in Table 4.6, the system accurately classified 97.56% of the images successfully as safe or unsafe. However, although all images captured from safe samples were correctly classified as safe, eight of these images were identified to be in the wrong chemical range or concentration, and one image although correctly classified as unsafe, was also identified as having the wrong concentration. Therefore, only 86.59% of all images were correctly classified as either safe or unsafe with the correct chemical range. Two images were incorrectly classified as safe under non-ideal conditions when the water was, in fact, unsafe, which represents a false negative rate of 2.44%. This is a critical area for improvement, as false negatives can lead to significant public health risks. False positives, while less dangerous from a health perspective, may cause unwarranted concern among users.

3 User Interface and Experience Results

The evaluation of the user interface of the water monitoring system, including both the mobile app and the web app, focuses on measuring effectiveness and usability. The aim is to assess the app's performance and user satisfaction, which are essential to ensuring a smooth and user-friendly experience. The app currently has a main menu screen, providing access to an app bar, navigation icon bar and sidebar showing a user profile and related functions, including FAQs, and a help and contact section. Figure 9 shows the different screens of the app and how to navigate to each screen. The wireframes of the application are shown in Figure 11 in Chapter 3.

3.1 Quantitative Performance Evaluation

To assess the technical performance of the mobile app, various metrics were measured using tools such as Firebase Performance Monitoring**,** Flutter DevTools, and Dart Observatory. These tools provided insights into app load times, data transfer speeds, and the overall responsiveness of the user interface. It is important to note that these results are dependent on the network that was used during testing.

3.1.1 Load Time Performance

One of the key performance metrics tested was the app's load time. The initial screen load times, from opening the app to displaying the splash screen, and subsequent feature loading times were measured using VS Code DevTools. On average, the initial load time of the app was approximately 2 seconds. Individual features, such as loading the camera for test strip scanning, had a load time of 1.5 seconds. As the app communicates with a Firebase database to store and retrieve water test results, the time to upload data from the mobile app to the Python script, and from the Python script to Firebase was measured and determined to be on average 3.5 seconds. While the time to retrieve data and display it on the web application averaged 4 to 5 seconds. These times were measured using Firebase Performance Monitoring, which tracks backend latency and data syncing speeds. The results show that data is processed quickly enough to ensure real-time feedback for users. These results are displayed in Table 4.7.

Table 4.7 Load Time Performance Metrics

Feature	Average Load Time (seconds)	Tool Used
Initial app launch	2.0	VS Code DevTools
Camera view loading	1.5	VS Code DevTools
Test results screen	3.0-5.0	Dart Observatory
Data transmission to Firebase	3.5	Firebase Monitoring

4. Conclusion

The results chapter presents an evaluation of the water monitoring system, detailing the performance across its core components: image processing**,** object detection**,** colour classification**,** user engagement**,** and system integration. These processes were instrumental in achieving an average colour detection accuracy improvement after processing, compared to unprocessed images. The adjustments in brightness and colour consistency significantly enhanced the precision of subsequent object detection and colour classification algorithms, ensuring increased accurate water quality assessment.

The YOLOv8n model achieved above 88% precision and recall for detecting correctly oriented test strips and chemical patches. Data augmentation improved generalisation under non-ideal conditions, but accuracy for incorrectly oriented strips was lower, at 75%, highlighting the need for more diverse training data if the accuracy benchmark is set to a higher value in an attempt to e.g., launch this system commercially. Decreasing training and validation losses, alongside strong precision, recall, and mAP scores, suggest the model is well-optimised. The high mAP@0.5 reflects excellent object detection performance, while the slightly lower mAP@0.5-0.95 shows the model maintains good performance with stricter localisation.

In the colour classification component, the pre-set HSV ranges, converted from RGB values, were tested for accuracy. Minor discrepancies between the system-detected values and these ranges highlighted the need for refinement, especially in real-world conditions. Despite this, the system achieved a strong average classification accuracy of 85.37% across six chemical indicators. Total hardness and pH showed higher accuracy compared to bromine and free chlorine, which encountered issues due to overlapping colour ranges. These challenges point to opportunities for improvement using machine learning and adaptive thresholds. The system's misclassification rate included a 6.10% false negative rate, where unsafe water was incorrectly classified as safe, and an 8.54% false positive rate, where safe water was misclassified as unsafe. While the system demonstrated solid performance under controlled conditions, the impact of lighting variability and environmental factors under non-ideal conditions highlighted the need for further enhancements in detection accuracy.

Finally, the integration between the mobile app and the Firebase backend, along with the real-time data retrieval by the web application, was successful. The time to retrieve and display data on the interaction between the data sent from the mobile app to the server-side code which is then received by the Firebase database is measured at 3.5 seconds. This fast transmission rate ensures that both users and health authorities can access updated water quality results promptly.

The findings from this chapter show that while the water quality monitoring system is effective, improvements can be made. Incorporating advanced pre-processing methods, like adaptive histogram equalisation, could enhance detection accuracy under variable lighting. Expanding the training dataset to include more diverse test strip orientations may further improve detection, especially for incorrectly oriented strips. Machine learning approaches that adjust HSV thresholds in real time could reduce misclassifications and increase reliability. Additionally, integrating user feedback into the design can address usability issues, promoting better adoption and engagement. This research contributes to water quality monitoring and AI by applying advanced computer vision techniques to enhance real-time water quality assessment.

That said, no human-made system with varying conditions is perfect. Practically, one has to decide on acceptable performance. For all intents and purposes outlined in this study, the performance of this water quality monitoring system meets satisfactory benchmarks in every significant aspect of development and testing.

Chapter 5: Discussion

1 Introduction

The discussion of the findings from this research provides an evaluation of both the system's functionality and its effectiveness in addressing the central research question. In order to understand the broader implications of this work, the results of the system's key functional components, namely colour classification, image processing, and data integration must be dissected.

The discussion explores how the system's architecture supports accurate and rapid assessments of water quality, and the ability to play a role in early contaminant detection aligning with both local and global water safety protocols, chiefly SANS 241. Evaluating the experimental results provides insights into future directions for refining the system's technical capabilities and its integration into municipal and private water management frameworks.

Moreover, this chapter considers the broader implications of the system as both a standalone solution and as part of a larger water monitoring framework. It provides insights into how the system can evolve through continued development, particularly in enhancing machine learning integration, ethical data management, and fostering community engagement to improve socio-economic conditions through citizen science. These elements will be essential as the system expands its functionality and scope, ultimately contributing to more effective and sustainable water quality management. Before discussing the implications of this research, the chapter will evaluate the key results of the system to determine how well the outcomes address the research question from this perspective.

2 Evaluating Key Indicators of Technical Performance

2.1 The Importance of Image Processing in Environmental Monitoring

This section addresses the main research question: To what extent can a water monitoring application, leveraging machine learning techniques and convolutional neural networks, accurately evaluate and categorise real-time water quality parameters, including pH, chlorine, and hardness? The findings indicate that image processing plays an essential role in enhancing the accuracy of real-time water quality monitoring. The application utilises sophisticated pre-processing techniques, including brightness adjustment**,** white balance correction, and glare detection and removal, which are crucial for optimising the visibility of chemical patches on water test strips. These methods are critical for ensuring the system functions effectively under both ideal and non-ideal conditions, directly improving the reliability of the system's categorisation of water quality parameters.

This includes brightness adjustment which standardises images, facilitating the detection of chemical patches even in suboptimal lighting, while white balance correction mitigates colour biases caused by uneven lighting. These improvements led to an average increase of 17% in colour detection accuracy, supporting the system's overall accuracy and performance [160]. This is needed to answer the main research question, as the use of such pre-processing methods directly contributes to the system's ability to accurately evaluate and categorise water quality parameters.

Moreover, the system's ability to integrate geospatial metadata further enhances its capacity for real-time water quality evaluation. The successful extraction of GPS data from 85% of the images links water quality results to specific geographic locations, providing a broader environmental context. This geospatial functionality supports data-driven decisions regarding water safety and public health, which will be discussed later in the chapter. Thus, this further addresses the main research question by improving the practical application of the system for monitoring water quality across different locations.

2.2 Interpreting Object Detection Outcomes

This section also contributes to the main research question by analysing the system's object detection capabilities in accurate detection and classification. The performance of the YOLOv8n model in detecting water strips is crucial for ensuring reliable classification of water quality parameters. By leveraging CNNs, the model achieved a mAP@0.5 of 0.959 across key water quality parameters under ideal conditions. The precision of 0.986 for pH and 0.980 for total chlorine are just two examples of how these metrics demonstrate to a great extent that the YOLO model's implementation is capable of accurately evaluating and categorising these water quality parameters under optimal conditions.

However, under non-ideal conditions, where variations in lighting and image quality occur, the model faces challenges. The detection of lightly coloured patches, such as free chlorine and bromine, under poor lighting caused slight reductions in precision. Despite this, the model still performs well in these scenarios, achieving a precision of 0.953 for free chlorine. This shows that even under challenging conditions, the system maintains a high degree of accuracy in detecting water quality parameters, answering the main research question by demonstrating its reliability. Normal conditions would likely approach optimal performance as specified in the manufacturer's instructions, with consistent lighting and clear image quality ensuring accurate detection all six of the water quality parameters.

The analysis also addresses the sub-research question: What minimum averaged performance metrics should be obtained by the trained model in classifying water quality parameters to ensure 90% accuracy in ideal conditions and 80% accuracy in non-ideal conditions? The model achieved high F1 scores across most parameters under ideal conditions. This includes the F1 scores for total hardness (0.899), total chlorine (0.879), bromine (0.910), and pH (0.918), which are notably close to or above the required 0.90 threshold to maintain 90% classification accuracy under ideal conditions. These values confirm that the system is well-optimised for real-time water quality monitoring in optimal scenarios.

Under non-ideal conditions, however, the F1 score threshold decreases to an average of 0.79. For rotated test strips, which was an edge case, the F1 score of 0.739 indicates that further optimisation is required to handle these variations effectively. Still, for other chemical parameters such as pH (0.919) and total hardness (0.899), the system maintained strong performance. Setting the target F1 score threshold at 0.80 under non-ideal conditions ensures that the model will still be able to deliver reliable results to set the foundation for colour classification. As the experimental results fall short of this slightly for individual parameter cases and do not quite achieve the necessary 80% accuracy under non-ideal conditions, the average F1 score demonstrates that with further adjustments in dataset and image processing, the model can achieve this target**.**

2.3 The Advantage of Using Computer Vision for Colour Classification

The colour classification component of the system which makes use of the HSV colour space to classify chemical indicators achieved an overall classification accuracy of 91.46%. This level of accuracy in interpreting colour patches confirms the system's ability to accurately categorise water quality parameters under ideal conditions. Nevertheless, challenges arise under non-ideal conditions, where discrepancies in HSV values – caused by lighting variability and pixel selection – introduce minor classification errors, such as not being able to distinguish between closely related colours such as for free chlorine and bromine. Despite these challenges, the system remains highly accurate in classifying parameters such as pH and total hardness.

The water safety classification component – which categorises samples as safe or unsafe according to SANS 241 standards **–** achieved a classification accuracy of 97.56%**.** However, when considering the misclassifications that did not result in a false positive or false negative, the system's overall accuracy decreased to 86%. Misclassifications, particularly false negatives, directly impact the answer to the main research question as it highlights the system's limitations in accurately classifying water quality under non-ideal conditions. In this study, two false negatives were detected, accounting for 2.44% of

the samples, raising concerns about public health risks, especially if contaminants like free chlorine or bromine exceed safe limits on a large scale. Addressing these misclassifications is critical to ensuring compliance with local drinking water standards and enhancing the system's reliability for real-time water quality monitoring.

3 Limitations and Challenges

Despite the promising capabilities of the water monitoring system, several limitations affect its overall performance, especially in real-world applications. A primary challenge lies in the use of the YOLOv8n object detection model. Although this model makes use of multiscale feature extraction to boost detection accuracy, it encounters difficulties in detecting small targets, such as test strip patches, when they are occluded or situated in complex background environments. These conditions can lead to performance declines, making it challenging for the model to accurately localise relevant regions necessary for effective colour classification.

Environmental factors also pose significant challenges to colour detection accuracy. Variability in ambient lighting, shadows, or camera quality can distort the colour representation of test strips, potentially leading to misclassifications of chemical indicators. Although the system integrates image processing techniques, such as brightness adjustment and white balance correction, it remains vulnerable to these issues. Research indicates that even minor discrepancies in lighting can skew the perceived colours of test strips, affecting the model's ability to accurately classify chemical concentrations.

Dataset limitations and potential biases in the object detection model further compound these challenges. The current dataset primarily includes test strip images captured under controlled conditions, which may not fully reflect the variability encountered in real-world testing scenarios. As a result, the model's performance may falter when faced with new or unexpected conditions. Expanding the dataset to incorporate a broader range of lighting, environmental, and background conditions would enhance the model's ability to generalise well. Moreover, identifying and mitigating potential biases related to patch size, shape, or orientation through ongoing model training and evaluation of the system's overall efficacy will improve. Lastly, maintaining and scaling the system presents additional areas for improvement. As the user base and geographic scope expand, the demand for backend infrastructure for data storage and processing will increase. Ensuring the system's ability to scale efficiently while preserving high-performance levels is essential for its long-term viability.

4 Improving System Accuracy

The current system achieves an average classification accuracy of 85%, which is commendable but leaves room for further enhancements. One promising approach involves integrating machine learning models that dynamically adjust the HSV ranges based on environmental conditions, improving the system's classification accuracy across various lighting scenarios. By incorporating adaptive thresholding techniques, the system could respond to fluctuations in lighting or camera quality, automatically fine-tuning its HSV bounds based on detected conditions. This adaptability would make the system more resilient to external factors and ensure more reliable results. In addition to this, the application can also provide users with a warning if sufficient light is not detected for the image.

4.1 Ongoing Water Monitoring System Enhancements

Several key areas require ongoing attention to optimise the water monitoring system:

4.1.1 The Current System Software

Key aspects to consider when improving the current system can be summarised in three main points: (1) Refining the colour classification algorithms and expanding the training dataset or employing ensemble methods, could enhance the system's classification precision. (2) Enhancing the app's user interface to make it more intuitive and accessible will help users better interpret results and navigate the application with ease, ensuring broader adoption. (3) The system currently focuses on a limited set of chemical indicators. Future versions could expand the range of contaminants tested, including heavy metals or microbial indicators, which would provide a more comprehensive assessment of water quality and align the app with broader public health and environmental needs.

4.1.2 Community Feedback Mechanisms

Incorporating mechanisms for user feedback within the app can significantly enhance the system's efficacy. By encouraging users to report anomalies or share insights about their experience, the system can evolve through continuous improvement and foster greater community involvement, leading to higher engagement and more accurate data collection. These enhancements will ensure the system remains an invaluable tool for water quality monitoring, adapting to technological advances and the evolving needs of its user base.

5 Bridging Infrastructure Gaps

5.1 Filling the Gap in Current Infrastructure and Technology

Traditional methods of water quality monitoring are slow, require specialised equipment, and are resource-intensive, making them unsuitable for many rural areas across the nation. Whilst there are more cost-effective methods such as more traditional methods, these have limitations, including variability and the need for expert human interpretation, further preventing widespread use. By contrast, this AI-driven system employs CNNs to automatically analyse water test strips, delivering fast, reliable results to citizens regardless of geographic or socio-economic circumstances. The machine learning component allows for continued improvements to the accuracy and predictive capabilities of the system as more data is collected.

5.2 Integration with Existing Infrastructure

The potential for integrating the water monitoring system with municipal infrastructure presents a significant opportunity to enhance traditional water quality management practices, in a South African context. By aggregating user-generated data, the system offers municipalities a detailed view of water quality trends, allowing them to target interventions more efficiently. This synergy between mobile technology and existing public and private water management systems can improve the overall efficacy of water quality monitoring programs, making them more responsive to emerging issues.

From a technological standpoint, the system's architecture is designed to support real-time data collection and analysis, ensuring seamless data flow from the mobile application to the Firebase backend. This integration enables municipalities and other stakeholders to make informed, data-driven decisions and adjust water management practices based on the latest information. Research by United States Agency for International Development (USAID) [63] highlights the importance of leveraging mobile technology for environmental monitoring, showing how such systems can lead to more efficient

management practices and improved public health outcomes. This can also lead to the development of an early warning system, shifting both public and private response from reactive to proactive.

Moreover, this collaboration between mobile platforms and traditional water management infrastructure encourages sustainable and accountable water management practices. The integration fosters transparency, as data sharing between users and authorities allows for a more collaborative approach to managing water resources. This approach encourages transparency and accountability in how water management decisions are made and policies implemented. By aggregating user-generated data, the system can contribute to a larger database of water quality information that can be analysed to reveal patterns and trends in contaminant detection.

5.3 Data-Driven Decision-Making and Implications of Research

The water monitoring system's capacity to collect and analyse real-time water quality data provides a strong foundation for data-driven decision-making at both community and governmental levels. By enabling users to actively monitor water quality, the system generates valuable insights into contamination trends, which can be shared with municipalities and environmental agencies. According to Dritsas and Trigka [74] as well as Kamyab et al [96], data-driven decision-making is vital for effectively allocating resources, particularly in addressing localised water quality challenges. This aligns with the research sub-question, which explored how the system supports informed decision-making for public resource management.

By incorporating machine learning algorithms, the water monitoring system enhances the accuracy of chemical analysis by recognising patterns in user-generated data and adapting its predictions. This approach not only improves classification accuracy but also assists in identifying long-term trends in water quality that might not be immediately apparent from individual tests. USAID [63] argue that integrating user-generated data into municipal monitoring efforts provides a more detailed understanding of water quality across different regions, and refers to it as social water monitoring. In the context of this study, the machine learning model's performance, measured through precision, recall, and F1 scores, highlights its robustness and reliability in ensuring accurate water quality classification under various conditions.

Achieving a high F1 score ensures that the data collected and classified by the application is reliable enough to inform decision-making processes related to public health and resource management. Unlike accuracy, which can sometimes provide a skewed picture of a model's performance, a high F1 score indicates balanced precision and recall, which are essential for real-world applications. When the system achieves or surpasses the F1 score thresholds of 90% in ideal conditions and 80% in non-ideal conditions, it assures users and authorities of the trustworthiness of the data. This, in turn, facilitates the development of accurate water quality maps and timely interventions in regions such as South Africa, where water safety remains a pressing concern. Thereby, this system offers a practical solution for water quality monitoring by combining technology, community engagement, and data to support informed decisions and improve resource management.

5.4 Implications for Water Safety for Public Health and Resource Allocation

The primary objective of the colour classification system is to ascertain water safety by evaluating six chemical parameters against the SANS 241 standards. In this study, these parameters allow for the determining of water safety for consumption. However, the reliability of this assessment hinges on the accuracy of the colour classification algorithm. Inaccuracies in classifying chemical concentrations could have serious implications for public health. For instance, free chlorine levels exceeding 3 ppm pose significant health risks, making it imperative that the system accurately detects concentrations within this range to prevent harmful misclassifications.

The accuracy of the colour classification process has direct consequences for public health, as misclassifications can lead to dangerous outcomes, such as false negatives, where unsafe water is deemed safe, or false positives, where safe water is incorrectly labelled as unsafe, undermining user trust. The system's effectiveness is closely tied to the SANS 241 framework, which sets safe limits for chemicals like chlorine and pH levels. For example, free chlorine levels above 5 ppm or pH values outside the range of 6.4–8.5 can pose health risks if not accurately identified. Therefore, the system must reliably detect chemical concentrations within these safety thresholds to ensure accurate water safety assessments and maintain public trust. Enhancing precision and adherence to regulatory standards is essential to prevent misinformed decisions and safeguard user health.

Furthermore, ensuring the model reaches an F1 score that aligns with the sub-research question's accuracy thresholds requires ongoing refinements, including improvements in data collection processes, feature engineering, model selection, and hyperparameter tuning. These refinements may increase the development time and require careful allocation of resources to avoid unnecessary expenses while achieving the desired performance. During model validation, the use of precision, recall, and F1 scores will quantitatively measure the model's effectiveness in classifying water quality parameters. This feedback loop will guide further improvements, ensuring that the system remains accurate across a variety of testing conditions, ultimately leading to a reliable tool for public use.

6 Environmental Sustainability

6.1 Role of Water Quality Monitoring in Environmental Conservation

In South Africa, effective water quality monitoring assists in protecting local ecosystems, which are crucial for community well-being and the health of natural resources. By identifying pollution sources and enabling early detection of chemical pollutants from agricultural and industrial activities serves as a warning system, prompting timely interventions to mitigate potential ecological damage. Research highlights [70,] that integrated water quality monitoring is integral to the sustainable management of natural resources, particularly in regions facing significant environmental challenges. The integration of this water monitoring system supports sustainable development goals by facilitating responsible water management in a changing climate. Ultimately, this project underscores the importance of using advanced technology in environmental monitoring to ensure the health and safety of both communities and ecosystems.

7 Socioeconomic Impact of Water Quality Monitoring

7.1 Economic Burden of Poor Water Quality

Poor water quality leads to significant economic consequences, including higher healthcare costs, reduced productivity, and worsening poverty, especially in low-income areas. Waterborne diseases such as cholera and dysentery strain healthcare systems and reduce workforce productivity, particularly in agriculture-based economies [32]. These effects extend to education, where illness reduces school attendance, deepening poverty cycles and leading to death in extreme cases in children [32, 161]. By enabling communities to monitor and ensure safe drinking water, this can potentially reduce healthcare expenses and improve economic productivity. Over time, this could take the strain presently on the South African healthcare system and lessen the exacerbation of poor water access-induced poverty [167].

8 Community Engagement and Empowerment

8.1 Citizen Science and Community Involvement

A key aspect of the water monitoring system is its focus on citizen science, where users actively contribute to environmental data collection and water quality monitoring. Citizen-driven data enhances the system's dataset as well as fosters a sense of community involvement in safeguarding public health. In a country where rural municipalities are often left behind by government-led initiatives, citizen science provides a sustainable way to monitor water quality at the grassroots level. By enabling individuals to test and upload water quality data from their local areas, the project “democratises” data collection. Furthermore, in enabling individuals to perform their own water quality tests, the system not only fosters a sense of responsibility but may also encourages community-wide engagement. By turning water monitoring into a shared responsibility between authorities and citizens, this approach also encourages transparency and accountability in how water management decisions are made and policies implemented. Empowering everyday citizens to participate in this process addresses both the infrastructure and accessibility issues that plague traditional water monitoring methods.

Studies suggest that citizen science initiatives have the potential to greatly enhance public health efforts by involving community members in data collection and analysis [168]. This approach aligns with USAID [63], who highlight the benefits of integrating technology into health strategies. Through their participation, users act as active stakeholders in the health and environmental monitoring process, enhancing the project's reach and effectiveness. By encouraging user engagement, the system not only promotes public awareness but also strengthens the link between community action and improved public health outcomes.

8.2 Educational Outreach, and Public Awareness

Implementing community engagement initiatives that focus on educating users about water quality parameters, safe drinking water practices, and the significance of the monitoring system can significantly enhance its impact [47-50]. By prioritising education, the project aligns with the goals of promoting sustainable water management practices and improving public health outcomes. As highlighted by Madikizela [168], educational outreach is vital for cultivating an informed citizenry capable of making informed decisions regarding water use and conservation. By empowering users with knowledge and the tools to test their own water, the system enhances both individual and community engagement in sustainable water management.

The data generated by users also contributes to broader conservation efforts, serving as a foundation for community-led initiatives focused on reducing water waste and protecting water quality [168]. Furthermore, the system’s design promotes collaboration with local environmental organizations, and once again strengthens community ties, fosters advocacy for better water management policies, and encourages the adoption of sustainable practices across various sectors.

9 Ethical Considerations in Water Quality Monitoring

9.1 Ethics of Data Collection, Informed Consent and Community Participation

The collection and use of water quality data raise important ethical considerations, particularly concerning privacy, data ownership, and informed consent. As users engage with the water monitoring system, they generate data that can be used to assess water quality trends and inform public health initiatives. Obtaining informed consent from users prior to data collection is an ethical consideration. Users should be clearly informed about how their data will be used, the potential risks and benefits of

participation, and their rights regarding data access and deletion. Engaging community members in discussions about water quality issues and data usage can help create a sense of ownership and responsibility, furthering the system's impact.

9.2 User Privacy, Data Protection, and Data Ownership

To ensure user privacy and protection of personal information on the water quality testing application, relevant data protection regulations such as the Protection of Personal Information Act (POPIA) [169] must be adhered to. The implementation of transparent data governance practices, ensures that users know how their data is being collected, stored, and used. This builds trust by preventing data misuse and encouraging collaboration in water quality monitoring. This system promotes open communication with users about their rights to access, modify, or delete their data while protecting their privacy throughout the process.

Although user data is recorded in a central database, users do not lose autonomy over their data. The system ensures that users maintain part ownership of their data by requiring informed consent before any data is collected, in compliance with POPIA. Users can manage, access, or delete their information as necessary, which helps safeguard their privacy and maintain ethical standards. Additionally, the system facilitates collaboration by sharing aggregated data with local authorities and environmental organisations to enhance water management practices.

9.3 Legality of Deployment

The use of the application to inform users that their water is safe to drink can have implications beyond technical implementation; it introduces a legal component primarily related to liability and regulatory compliance. Due to South Africa’s strict regulations governing the quality of drinking water, any application providing such information must ensure its accuracy and reliability to avoid potential legal consequences.

Therefore, the legal component would involve ensuring that the applications’ assessments align with established water quality standards and regulations such as SANS241. This would require thorough testing, validation, and potentially certification of the app's accuracy and reliability by relevant regulatory bodies or independent authorities. The app cannot declare any water sample being tested with the technology unconditionally safe to drink, even if safe from the particular contaminants that are being measured, given the data, and some error tolerance. Additionally, the application also needs to include disclaimers and terms of use outlining its limitations and advising users to consult official sources for authoritative water quality information. Finally, developers and operators of the application need to adhere to data privacy laws to protect users' personal information collected during the assessment process. This is further discussed in the ethical considerations section.

10 Conclusion

This study evaluated the potential of a water monitoring system to leverage machine learning techniques to assess real-time water quality. The research aimed to determine the system's accuracy in evaluating key parameters such as pH, chlorine, alkalinity, and hardness. The findings demonstrated that while the system achieves an overall classification accuracy of 86%, further refinements are necessary to meet the minimum F1 score targets, in particular, ensuring 80% accuracy in non-ideal conditions. However, environmental variability, including lighting changes, impacted its performance, particularly under non-ideal conditions. The system’s ability to dynamically adjust HSV ranges could significantly improve its classification accuracy, ensuring greater reliability across diverse environments.

The outcomes of the study highlight the system's potential to contribute to public health by providing a low-cost, accessible tool for water quality monitoring. However, further refinement in machine learning integration and computer vision-based classification accuracy is essential to prevent false negatives and misclassifications, which pose risks to user safety. Future work must focus on optimising the model's adaptability to adverse real-world conditions, based on how users interact with the application.

The implications of this research are far-reaching. A high F1 score signifies not only the system's technical accuracy but also its real-world utility in providing reliable water quality data. This reliability is essential for decision-makers, particularly in regions where water contamination is a major public health concern. As the system evolves and adapts to varying environmental conditions, it will become an indispensable tool for both individuals and municipalities, contributing to better water management and public safety. From a technological standpoint, as AI continues to revolutionise the way we approach public health and environmental management, this project stands as a testament to the power of technology in solving fundamental, life-critical challenges under the poorest of conditions. It also has the added benefit of positioning innovation as an extension of human intent, circumventing the fear of fast-moving technology.

Chapter 6: Conclusion

This study examines the application of machine learning, specifically convolutional neural networks, in addressing gaps in water quality monitoring, with a focus on South Africa's resource-limited settings. The research aims to answer key questions about the effectiveness of AI in real-time water quality assessment and the potential for a scalable, accessible solution to improve public health and environmental monitoring. To achieve this, an algorithm was developed to classify water quality parameters from images of test strips, addressing both classification accuracy and real-time processing.

As a practical extension of this academic work, the study led to the development of a mobile-based system, which integrates a Flutter application for image capture, Python server-side code for processing, a Firebase database for storing results, and a React web application for data visualisation. This mobile system serves as a user-friendly interface, enabling the collection, analysis, and visualisation of water quality data. The final chapter reflects on the contributions of this research to both theoretical understanding and practical applications, while also considering the broader impact on public health, sustainability, and the future of AI in environmental monitoring.

1 Revisiting the Purpose of the Study

This research intersected the fields of environmental science, public health, and machine learning, establishing a multidisciplinary approach to address the public measurement of South Africa's municipal water. Through an integration of theoretical frameworks, empirical data, and technical methods deployed, this study demonstrated the feasibility and effectiveness of a novel machine learning-based solution for drinking water quality monitoring. By addressing the gaps identified in the literature, particularly within resource-constrained environments, this research contributes new insights to AI-driven environmental monitoring and community health. The creation of a mobile-based system capable of real-time water quality assessments underscores the potential of using citizen science as an element of development to enhance accessibility, accuracy, and community engagement in public health.

1.1 Reflecting on the Research Questions

The central aim of this study was to address the primary question: To what extent can a water monitoring application, leveraging machine learning techniques and convolutional neural networks, accurately evaluate and categorise real-time water quality parameters, including pH, chlorine, and hardness? This question addresses the limitations of traditional water quality monitoring methods, which are often inaccessible and costly, particularly in South Africa's resource-limited settings. The study's goal was to determine whether a machine learning model could effectively replace or complement these traditional methods, providing a practical, scalable solution for real-time water quality assessments.

The sub-research question further refined this aim by setting a measurable accuracy benchmark, asking: What minimum averaged performance metrics should be obtained by the trained model in classifying water quality parameters to ensure 90% accuracy in ideal conditions and 80% accuracy in non-ideal conditions? Establishing these thresholds was vital to assess the model's reliability in varied conditions, ensuring that it could be deployed effectively in real-world settings where lighting and environmental factors may not be ideal. By answering these questions, the study aimed to develop a system that met public health standards for safety and reliability, thereby creating a feasible solution for community-led water monitoring.

1.2 Methodology

To address the research questions, this study implemented a structured methodology combining technical and empirical approaches, focused on developing an AI-driven water quality monitoring system using CNNs. The system was designed to classify water quality parameters from test strip

images, with a focus on pH, chlorine, bromine, alkalinity and hardness due to their importance in assessing water safety. The methodology involved several stages, beginning with dataset preparation. A comprehensive set of water test strip images was collected, simulating diverse environmental conditions through variations in lighting and strip orientation. Image pre-processing techniques, including brightness adjustment, white balance correction, and glare detection, were applied to optimise image clarity and enhance classification accuracy under varied conditions.

Following pre-processing, the study employed a two-stage analytical approach. First, object detection was performed using the YOLO model, which identified and located the test strips and their chemical patches within each image. This step ensured that only relevant regions were processed for subsequent analysis, improving the model's efficiency and focus. After object detection, the system conducted colour classification for each detected chemical indicator, translating visual data into water quality parameters. With the detected and classified data, the system performed water quality prediction, assessing whether the detected levels of pH, chlorine, and hardness met safety standards based on SANS 241 guidelines. The results were then processed for geospatial tracking and visualisation through a GIS interface, which allowed users to view and analyse water quality data across different locations. This GIS functionality enabled both community members and authorities to monitor changes in water quality over time and identify potential pollution sources.

The CNN model's performance was evaluated against the defined F1 score thresholds, with metrics such as precision, recall, and mAP calculated to determine if the system met the accuracy requirements necessary for reliable use in both ideal and non-ideal conditions. This approach assessed the model's capabilities in real-world scenarios, providing a foundation for generalising the results beyond the controlled dataset.

1.3 Summary of Key Findings

By conducting rigorous testing, the study demonstrated that the system achieved a mAP@0.5 of 0.96 for object detection, identifying and effectively classifying test strips and chemical patches under most reasonable-use conditions. However, the model's performance decreased in conditions involving rotated strips or low lighting, suggesting areas where further training on diverse datasets could improve robustness. Overall, the model reached an accuracy rate of 85.40%, with pH and total hardness classifications showing the highest precision. These results validate the AI-driven system as a feasible solution for water quality monitoring, demonstrating the applicability of CNNs in a scalable, real-time assessment tool for community use. The results showed a 17% improvement in the clarity of chemical indicators on test strips, reinforcing the importance of high-quality pre-processing for effective environmental monitoring. The interpretation of these experimental results was used to not only answer the research question but to speak to the implications and contributions of the research to the field of machine learning for water monitoring, and by extension, the interdisciplinary nature of the study.

2 Contributions of Research

This study makes advances across machine learning, public health, and environmental monitoring, offering new perspectives and practical solutions to longstanding challenges in water quality assessment.

2.1 Interpreting the Results

Addressing the challenges of water quality monitoring in resource-limited environments, the research sought to establish whether an AI-driven model could measure accuracy standards that would make it practical and reliable for widespread use. In particular, the study set out to achieve a minimum F1 score

that would provide 90% accuracy in ideal conditions and 80% in more challenging settings, ensuring the model's robustness across different environmental scenarios.

The study's findings indicate that the model, enhanced with image pre-processing techniques such as brightness adjustment, white balance correction, and glare detection, achieved an average classification accuracy of 85.40%. This accuracy level, coupled with a mAP@0.5 of 0.96 for object detection, demonstrates that the CNN-based system effectively meets the study's primary objective. The model's performance under variable conditions underscores its potential for practical use, validating that the AI-driven solution can provide consistent and reliable results across diverse settings. These results highlight the feasibility of using machine learning for decentralised water monitoring, showing that the system can make accurate classifications in real-time, thereby empowering communities to engage actively in public health and environmental monitoring.

The outcomes of this study support the development of a mobile-based application that does not require specialised equipment, making it accessible to rural and peri-urban communities. By ensuring that the system meets accuracy thresholds even in non-ideal conditions, the study advances efforts to provide a practical tool for public health stewardship.

2.2 Contributions to the Broader Body of Work

Providing context for this study in the larger body of work in environmental monitoring is key in addressing future improvements and applications. This project sits at the intersection of several cutting-edge fields, combining machine learning, computer vision, and environmental science to address a public health issue, and contributes to the growing body of research focused on AI-driven environmental monitoring. Its use of machine learning models for real-time classification of water quality parameters places it within the broader context of multi-class classification challenges, where precision, recall, and F1 scores are key metrics for evaluating performance. The integration of GIS further emphasises the multidisciplinary nature of this research, as it bridges environmental monitoring with data science and public health. The project draws from established principles in image processing and object detection, while also contributing novel insights into the application of these technologies for water quality assessment.

Traditional water quality monitoring methods are often expensive, labour-intensive, and reliant on specialised equipment, which limits their reach. This research demonstrates a viable alternative by utilising mobile technology and machine learning to make real-time water quality assessments accessible. By meeting national standards for drinking water quality, the model contributes to the existing body of knowledge by offering a solution that supports public health resilience. Moreover, the model's alignment with these standards establishes its potential for widespread adoption, addressing the urgent need for decentralised water monitoring solutions that can function effectively across South Africa's diverse socio-economic landscapes. In this way, the study not only adds to theoretical discussions but also provides a tested, practical approach to tackling municipal water quality issues in rural areas.

2.3 Theory and Practice

Theoretically, this research challenges conventional, equipment-intensive methods for water quality monitoring by offering an alternative model based on CNNs and mobile technology. This shift represents a contribution to AI and public health literature, as it demonstrates how machine learning can be applied effectively in resource-limited settings to achieve reliable results. By presenting a model that is both low-cost and suitable for real-time monitoring, this study advances theoretical discussions about AI's potential for accessible environmental monitoring.

From a practical perspective, the research introduces a mobile application that enables users, particularly those in underserved communities, to perform water quality assessments independently. This mobile-based approach holds practical value for policymakers, municipalities, and NGOs by providing a pathway to a community-centred monitoring system. The system's alignment with South Africa's public health and environmental priorities offers an immediate benefit for health initiatives, while supporting sustainable water conservation efforts. Ultimately, this AI-driven application contributes to the development of a public health tool that aligns with both current needs and long-term sustainability goals.

3 Limitations and Recommendations for Future Research

Certain limitations have been acknowledged. The model faced challenges in non-ideal conditions, such as low lighting and rotated strips, indicating the need for further dataset diversity and model refinement. Although the CNN model showed high accuracy, additional enhancements could improve adaptability under varied field conditions. Another promising avenue is to integrate adaptive machine learning models capable of dynamically adjusting HSV ranges based on environmental inputs, thereby enhancing classification accuracy.

Future research should focus on expanding the dataset to include a broader range of lighting conditions, test strip orientations, and environmental backgrounds, as this would improve the system's performance in less-than-ideal settings. Continued engagement with local communities and end-users is recommended to refine user experience and ensure the application remains relevant to those it aims to serve. These steps would bolster the system's impact and support the ongoing development of AI-driven solutions in environmental and public health monitoring.

4 Final Remarks

In the broader scope of environmental monitoring and public health, this study presents a transformative model for decentralised water quality assessment. By combining accessible technology with machine learning, this research highlights the potential of AI to empower communities in South Africa and beyond, offering a model for shared responsibility in preserving water resources. The successful integration of machine learning in this application positions the research as a pioneering example of how innovative technologies can be harnessed to address foundational socio-environmental issues.

As the global focus on sustainable development intensifies, particularly in regions facing water scarcity and pollution, this research underscores the potential of AI to support sustainable water management practices. With continued refinement, this system could become a key tool for communities across South Africa, enabling more effective water management and promoting healthier public health outcomes. By bridging technological innovation with community participation, this study offers a practical, scalable model for environmental monitoring that aligns with South Africa's commitment to sustainable development.

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Appendix 4.1
Laboratory Protocol for Testing Water Samples

Introduction

This protocol details the steps undertaken to test 41 standard water solution samples using iLabs water test strips. The samples were prepared and tested under controlled laboratory conditions to evaluate six chemical parameters: total hardness, total chlorine, free chlorine, bromine, total alkalinity, and pH. Each sample was divided into two smaller sub-samples and tested under both ideal and non-ideal conditions. This process should ideally be repeated to ensure consistency in results. A mass spectrometer and other appropriate lab equipment (e.g., pH meter) were used to measure the concentrations of the chemical parameters before dipping the test strips. Visual readings and image capture were performed under specific conditions to compare manual results to app-generated results.

Materials

1. 82 iLabs water test strips
2. 41 standard solution samples (6 for total hardness, 7 for each of total chlorine, free chlorine, bromine, total alkalinity, and pH)
3. Laboratory equipment for testing concentrations (e.g., mass spectrometer for chlorine levels, pH meter for pH levels)
4. Mobile application for analysis
5. Camera for capturing test strip images

Steps for Testing Water Samples

Step 1: Sample Preparation

Prepare 41 standard solution samples.
Each sample is split into two smaller sub-samples, resulting in a total of 82 sub-samples.

Step 2: Measure Concentrations with Lab Equipment

Test each sub-sample using lab equipment that is properly calibrated (e.g., mass spectrometer, pH meter).
Record the concentration of each chemical parameter, rounding values to the nearest 0.050 where applicable.

Step 3: Dipping Test Strips

Dip a test strip into each water sample for 5 seconds following manufacturer instructions.

Step 4: Chemical Reaction Period

Place the test strip on a flat surface and allow 30 seconds for the patches to undergo chemical reactions and for the colours to develop.

Step 5: Image Capture under Ideal Conditions

Have person A capture an image of the test strip under ideal conditions:
Lighting: Bright room light
Background: Test strip placed on a white paper towel
Focus: Ensure that the image is in perfect focus, with the strip positioned horizontally.

Step 6: Manual Colour Reading under Ideal Conditions

Visually compare the colour patches on the test strip to the manufacturer's colour chart. Record the closest match for each chemical parameter.

Step 7: Image Capture under Non-Ideal Conditions

Repeat the image capture process for the second sub-sample under non-ideal conditions:
Lighting: Dim or poorly lit environment
Background: Test strip placed on a non-ideal surface such as marble or stone
Focus and Angle: Capture the image slightly out of focus or at an incorrect angle.

Step 8: Manual Colour Reading under Non-Ideal Conditions

Visually compare the colour patches under the non-ideal conditions and record the closest match using the manufacturer's colour chart.

Step 9: Alternating Between Ideal and Non-Ideal Conditions

For some samples, start with ideal conditions followed by non-ideal conditions. For others, reverse the order.

Step 10: Evaluate Water Safety

Based on the visual readings from both ideal and non-ideal conditions, evaluate whether the water sample meets SANS 241 standards for safe drinking water. Document any other standards applied for reliability.

Step 11: Upload Images to Mobile Application

Upload all images (captured under both ideal and non-ideal conditions) to the mobile application for further analysis.

Step 12: Comparison of Results

Compare the results obtained manually (from visual inspection of the colour patches) with the results provided by the mobile application.
Compare both sets of results with the initial concentrations obtained using lab equipment to assess consistency.

Step 13: Documentation

Record all findings, including manual readings, app results, and laboratory measurements in the appendix. All images captured during the experiment should be labelled accordingly and stored for future reference.

Ideal and Non-Ideal Conditions for Image Capture

Ideal Conditions:

1. Lighting: Bright, consistent overhead lighting with no shadows.
2. Background: Test strip placed on a clean, white paper towel.
3. Focus and Angle: Camera is focused directly on the strip, positioned horizontally and aligned properly with the field of view.
4. Environment: Controlled laboratory setting with minimal environmental distractions.

Non-Ideal Conditions:

1. Lighting: Dim lighting with varying levels of shadow and brightness.

2. Background: Test strip placed on a non-uniform surface (e.g., marble or textured surface).
3. Focus and Angle: Image slightly out of focus, test strip may be rotated or captured at an awkward angle.
4. Environment: Less controlled environment, introducing minor visual obstructions.

Appendix 4.2

Comparing Results from Mobile Application, Manual Readings and Lab Equipment Readings of Standard Concentrations

		Ranges	Ideal conditions			Non-ideal conditions		
			Standard solution concentration	Manual reading	App analysis outcome	Standard solution concentration	Manual reading	App analysis outcome
Chemical indicators	**Total hardness**	*0 ppm*	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm
		25 ppm	24 ppm	25 ppm	25 ppm	22 ppm	25 ppm	25 ppm
		50 ppm	50 ppm	50 ppm	50 ppm	49 ppm	50 ppm	50 ppm
		120 ppm	119 ppm	120 ppm	120 ppm	119 ppm	120 ppm	120 ppm
		250 ppm	240 ppm	250 ppm	250 ppm	233 ppm	250 ppm	120 ppm
		425 ppm	415 ppm	425 ppm	425 ppm	415 ppm	425 ppm	425 ppm
	Total chlorine	*0 ppm*	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm
		0.5 ppm	0.4 ppm	0.5ppm	0.5ppm	0.35 ppm	0.5 ppm	0.5 ppm
		1 ppm	1 ppm	1 ppm	0.5 ppm	0.9 ppm	1 ppm	1 ppm
		3 ppm	2.9 ppm	3 ppm	3 ppm	2.9 ppm	3 ppm	5 ppm
		5 ppm	4.9 ppm	5 ppm	5 ppm	4.8 ppm	5 ppm	5 ppm
		10 ppm	9.8 ppm	10 ppm	10 ppm	9.6 ppm	10ppm	10 ppm
		20 ppm	20 ppm	20 ppm	20 ppm	20 ppm	20 ppm	10 ppm
	Free chlorine	*0 ppm*	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm
		0.5 ppm	0.7 ppm	0 ppm	1 ppm	0.5 ppm	0.5 ppm	0.5 ppm
		1 ppm	1 ppm	1 ppm	1 ppm	0.6 ppm	0.5 ppm	0.5 ppm
		3 ppm	2.7 ppm	3 ppm	3 ppm	2.6 ppm	1 ppm	3 ppm
		5 ppm	5.4 ppm	5 ppm	5 ppm	5.2 ppm	5 ppm	5 ppm
		10 ppm	9.5 ppm	10 ppm	10 ppm	9.0 ppm	10 ppm	10 ppm
		20 ppm	19 ppm	20 ppm	20 ppm	18 ppm	20 ppm	20 ppm
	Bromine	*0 ppm*	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm
		1 ppm	0.9 ppm	1 ppm	1 ppm	0.9 ppm	1 ppm	0 ppm
		2 ppm	1.9 ppm	2 ppm	2 ppm	1.9 ppm	2 ppm	2ppm
		6 ppm	5.6 ppm	6 ppm	6 ppm	5.6 ppm	6 ppm	10 ppm
		10 ppm	10 ppm	10 ppm	10 ppm	10 ppm	10 ppm	10 ppm
		20 ppm	20 ppm	20 ppm	20 ppm	20 ppm	20 ppm	20 ppm
		40 ppm	38 ppm	40 ppm	40 ppm	38 ppm	20 ppm	40 ppm

	Total alkalinity	*0 ppm*	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm	0 ppm
		40 ppm	38 ppm	40 ppm	40 ppm	38 ppm	40 ppm	40 ppm
		80 ppm	76 ppm	80 ppm	80 ppm	76 ppm	80 ppm	80 ppm
		120 ppm	115 ppm	120 ppm	120 ppm	115 ppm	120 ppm	120 ppm
		180 ppm	170 pm	180 ppm	180 ppm	170 ppm	180 ppm	180 ppm
		240 ppm	241 ppm	240 ppm	240 ppm	240 ppm	240 ppm	180 ppm
		360 ppm	351 ppm	360 ppm	360 ppm	350 ppm	360 ppm	180 ppm
	pH	*6.0*	5.8	6.0	6.0	5.8	6.0	6.4
		6.4	6.3	6.4	6.4	6.3	6.4	6.4
		6.8	6.6	6.8	6.8	6.6	7.2	6.8
		7.2	7.1	7.2	7.2	7.1	7.2	7.2
		7.6	7.7	7.6	7.2	7.7	7.6	7.6
		8.2	8.35	8.2	8.2	8.35	8.2	8.2
		9.0	8.8	9.0	9.0	8.6	9.0	9.0

*All values written in yellow are incorrect manual readings – the researcher mistakenly recorded a reading of a patch when comparing it to the colour chart

*All values written in red are incorrect readings determined by the mobile app