MACHINE LEARNING-DRIVEN PREDICTIVE ANALYTICS FOR CHOLERA OUT-BREAKS FORECASTING AND RESOURCE OPTIMIZATION IN ZAMBIA'S HEALTH SECTOR

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ZCAS UNIVERSITY

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DECLARATION

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I hereby declare that this final year research project is the result of my own work, except for quotations and summaries which have been duly acknowledged.

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ABSTRACT

Healthcare systems worldwide are increasingly leveraging data-driven strategies to enhance decision-making, optimize resource allocation, and improve patient outcomes. This research explores the application of machine learning-driven predictive analytics for Cholera outbreaks forecasting and resource optimization in Zambia's healthcare sector. The study focuses on communicable diseases, particularly cholera, which remains a significant public health threat due to recurring outbreaks.

The research employs supervised learning algorithms, including Random Forest and Gradient Boosting, for cholera outbreak prediction and unsupervised learning techniques like K-Means for resource utilization analysis. Data will be sourced from historical health records, real-time hospital data, and external variables such as weather patterns, sanitation conditions, and population density. The model's performance will be evaluated using metrics like accuracy, precision, recall, and F1-score to ensure reliability and effectiveness.

By integrating predictive analytics into Zambia's healthcare system, this study aims to facilitate proactive decision-making, enabling healthcare administrators to anticipate cholera outbreaks and allocate resources efficiently. The findings will contribute to evidence-based healthcare management, aligning with global best practices while addressing Zambia's unique challenges. Ultimately, the project seeks to establish a scalable and sustainable predictive analytics framework to strengthen epidemic preparedness, enhance health system resilience, and improve patient care.

Keywords: *Predictive Analytics, Machine Learning, Cholera Outbreak Prediction, Communicable Diseases, Resource Optimization, Healthcare Management*

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DEDICATION

I would like to take this opportunity to express my deepest gratitude and appreciation to my family for their unwavering love, support, and encouragement throughout this journey.

I dedicate this work to my father, Vanny Himakoma Moonga, and my mother, Susan Choonga Chimuka Moonga, whose guidance, sacrifices, and wisdom have shaped me into the person I am today. Their unwavering belief in my abilities has been a constant source of strength.

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To my children - Jayden Kabwenda Moonga, Jamira Pimpa Moonga and Jamal Banji Moonga - you are my greatest inspiration. May this work serve as a testament to the importance of perseverance, dedication, and the pursuit of knowledge.

This achievement is as much yours as it is mine.

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LIST OF ABBREVIATIONS

AI: Artificial Intelligence

APIs: Application Programming Interfaces

AUC-ROC: Area Under the Receiver Operating Characteristic Curve

BI: Behavioral Intention

CNN: Convolutional Neural Network

CSO: Central Statistical Office

DHIS2: District Health Information Software 2

DSR: Design Science Research

DT: Decision Trees

EDA: Exploratory Data Analysis

EHR: Electronic Health Record

ETL: Extract, Transform, Load

FN: False Negative

FP: False Positive

FPR: False Positive Rate

GBM: Gradient Boosting Machines

GDPR: General Data Protection Regulation

GNN: Graph Neural Networks

HIPAA: Health Insurance Portability and Accountability Act

HMIS: Health Management Information System

K-NN: k-Nearest Neighbors

LP: Linear Programming

LR: Logistic Regression

LSTM: Long Short-Term Memory

MCDA: Multi-Criteria Decision Analysis

ML: Machine Learning

MPC: Model Predictive Control

ORT: Oral Rehydration Therapy

PCA: Principal Component Analysis

PEOU: Perceived Ease of Use

PU: Perceived Usefulness

RBAC: Role-Based Access Control

RFE: Recursive Feature Elimination

RF: Random Forest

RNN: Recurrent Neural Network

RRI: Responsible Research and Innovation

SMOTE: Synthetic Minority Oversampling Technique

SVM: Support Vector Machine

TAM: Technology Acceptance Model

TB: Tuberculosis

TN: True Negative

TP: True Positive

UHC: Universal Health Coverage

WASH: Water, Sanitation, and Hygiene

WHO: World Health Organization

XGBoost: Extreme Gradient Boosting

ZNPHI: Zambia National Public Health Institute

CHAPTER 1

INTRODUCTION

1.1 Background to the study

In recent years, healthcare systems globally have increasingly turned to data-driven strategies to enhance decision-making, allocate resources more effectively, and improve patient outcomes. Predictive analytics, powered by machine learning, stands out as a transformative tool in this effort. By analyzing historical and real-time health data, predictive models can identify patterns, forecast disease outbreaks, and guide preventive measures, ultimately reducing the strain on healthcare systems and improving population health [7]-[9].

Zambia, like many developing nations, has faced persistent challenges with disease outbreaks, significantly impacting public health and the healthcare system. The country frequently experiences outbreaks of communicable diseases such as malaria, tuberculosis (TB), HIV/AIDS, and diarrheal diseases, which remain the leading causes of morbidity and mortality. Malaria is a significant public health problem in Zambia, with an estimated 3.7 million cases in 2021 (incidence rate of 189.7 cases per 1,000 people), resulting in 8,806 deaths. TB also poses a substantial burden, with an estimated 59,000 cases in 2020, corresponding to 307 cases per 100,000 population in 2021. HIV/AIDS remains a leading cause of death in Zambia [2]-[3].

Historical health statistics indicate that Zambia has been prone to periodic cholera outbreaks, particularly during the rainy season when sanitation conditions deteriorate. The last major outbreak, occurring between October 2017 and June 2018, resulted in 5,935 reported cases and 114 deaths. More recently, from October 2023 to February 2024, the country experienced another severe cholera outbreak, with 19,719 cases reported, underlining the persistent threat cholera poses. The impact of such outbreaks extends beyond health, affecting economic activities and placing immense pressure on limited medical resources [4]-[6].

Traditional approaches to managing cholera outbreaks in Zambia have often been reactive, involving emergency interventions once cases have already been reported. This approach typically includes:

- Rapid response measures such as emergency water sanitation and hygiene (WASH) interventions.
- Deployment of oral rehydration therapy (ORT) and antibiotics.

- Public awareness campaigns focusing on hygiene and safe drinking water.
- Vaccination programs in high-risk areas.

Despite these efforts, the response has often been delayed, leading to higher infection rates and increased mortality. For example, during past outbreaks, health authorities struggled with insufficient early warning systems, delayed resource mobilization, and gaps in surveillance data. The reactive nature of cholera management highlights the urgent need for innovative approaches that can predict and mitigate outbreaks before they escalate.

Machine learning offers a promising solution to these challenges by enabling proactive disease surveillance and outbreak prediction. By leveraging historical health records, environmental data, and real-time inputs, predictive models can identify high-risk areas and forecast potential cholera outbreaks with improved accuracy.

Key advantages of using machine learning for cholera outbreak prediction include:

- Early Warning Systems: Machine learning models can analyze weather patterns, water quality indicators, and past outbreak trends to detect potential risks before cases emerge.
- Resource Optimization: Predictive analytics allows health authorities to allocate medical supplies, personnel, and preventive measures more efficiently to areas most at risk.
- Enhanced Decision-Making: Real-time data processing can guide policymakers in designing more effective public health interventions, reducing the economic and social impact of cholera.

Implementing predictive analytics in Zambia's healthcare system aligns with global best practices for resource-constrained environments. However, the success of such models depends on access to reliable data, integration with existing health systems, and capacity-building among healthcare professionals. This study aims to develop and evaluate a predictive model tailored to the Zambian healthcare context, with the goal of improving health outcomes and strengthening epidemic preparedness. By harnessing the power of machine learning, Zambia can transition from reactive to proactive public health strategies, ultimately saving lives and ensuring a more resilient healthcare system.

1.2 Problem Statement

Healthcare systems in Zambia face significant challenges in managing disease outbreaks and optimizing the allocation of limited resources. These issues are particularly evident in the recurring outbreaks of cholera, a highly communicable disease that has caused substantial morbidity and mortality in the country. Cholera outbreaks are often exacerbated by poor sanitation, inadequate access to clean water, and seasonal climatic variations. The unpredictable nature of these outbreaks, combined with limited medical personnel and insufficient supplies, results in reactive rather than proactive responses. This approach frequently leads to delays in healthcare delivery, gaps in patient care, and inefficiencies in resource utilization [10]-[13].

Globally, machine learning-driven predictive analytics has demonstrated transformative potential in addressing similar challenges by enabling proactive healthcare management. By identifying patterns in historical and real-time health data, predictive models can forecast disease outbreaks and optimize resource distribution [8]-[9]. However, the Zambian health sector has not fully leveraged these advanced tools, partly due to limited infrastructure, technical expertise, and localized research [11].

This research seeks to address these gaps by developing and evaluating a machine learning-based predictive analytics model specifically tailored to cholera outbreak prediction and resource optimization in Zambia's healthcare system. The project aims to enable more accurate disease forecasting, early intervention, and efficient resource allocation, thereby enhancing the resilience and responsiveness of Zambia’s health system. This initiative aligns with the global shift toward data-driven healthcare management and has the potential to significantly reduce cholera-related morbidity and mortality while improving overall public health outcomes in resource-constrained environments.

Aim and Objectives of the Study

Aim

The aim of this research is to develop and evaluate a machine learning-based predictive analytics model to improve disease forecasting and resource allocation in Zambia’s health sector.

Objectives of the study

i. To design a machine learning model tailored to predict cholera outbreaks in Zambia based on historical health data, climate patterns and demographic factors.
ii. To design a resource allocation framework using predictive analytics.
iii. To test and evaluate the model's performance using real-world health data.
iv. To access the effectiveness and feasibility of integrating the predictive analytics model into Zambia's public health decision-making process for proactive intervention planning.

1.4 Research Questions

RQ1: *How accurately can machine learning models predict cholera outbreaks in Zambia using health data, climate patterns and demographic factors?*

RQ2: *How can predictive analytics be integrated with optimization techniques to allocate limited medical resources during cholera outbreaks?*

RQ3: *How do data quality challenges impact model performance and reliability, and what processing strategies can be used to mitigate these issues based on predictive metrics such as F1-Score, AUC/ROC?*

RQ4: *What are the potential benefits and challenges of integrating predictive machine learning analytics into Zambia's healthcare policy and resource management.*

1.5 Scope and Limitation

Scope of the Study

This study focuses on the development and evaluation of a machine learning-based predictive analytics model to enhance cholera outbreak forecasting and resource allocation in Zambia's healthcare sector. Specifically, the research will:

- Analyze historical and real-time health data to identify trends and patterns in cholera outbreaks, considering factors such as weather patterns, water quality, sanitation conditions, and past outbreak trends.

- Develop a predictive model using supervised learning techniques, such as Random Forest, Extreme Gradient Boosting (XGBoost), Logistic Regression and Long Short-Term Memory (LSTM) networks, to forecast cholera outbreaks with high accuracy.

- Optimize medical resource allocation by employing unsupervised learning methods, such as K-Means clustering and Principal Component Analysis (PCA), to ensure equitable distribution of medical supplies, personnel, and intervention efforts.3

- Evaluate the model's performance using metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) to ensure reliability in a real-world healthcare setting.

- Provide recommendations for integrating predictive analytics into Zambia's healthcare system, focusing on early outbreak detection and efficient resource distribution for long-term sustainability.

The study primarily targets public healthcare facilities in Zambia particularly those in Cholera Prone areas of Lusaka Province. It will utilize historical health records, real-time hospital data, environmental factors, and epidemiological reports to train and validate the predictive models.

Limitations of the Study

1. Data Quality and Availability: The effectiveness of Machine Learning models is highly dependent on the quality and availability of healthcare data. In many cases, healthcare datasets are incomplete, inconsistent, or biased, which can limit the accuracy and generalizability of ML models. Access to high-quality, diverse data sets remains a challenge [14].

2. Algorithmic Bias: ML models can inherit biases present in the training data, leading to unequal outcomes across different patient demographics. These biases can result in disparities in healthcare delivery, particularly for underrepresented or vulnerable populations, making it difficult to ensure fairness and equity in ML-driven healthcare solutions [14].

3. Integration with Existing Systems: Implementing ML technologies in healthcare often requires integration with legacy systems such as electronic health records (EHRs). Many healthcare providers face technical and organizational barriers to achieving seamless integration, which can slow down adoption and limit the scalability of ML solutions [14].

4. Regulatory and Ethical Concerns: The regulatory framework for ML in healthcare is still evolving, with uncertainties around approval processes, liability, and compliance. Ethical concerns related to patient privacy, data security, and informed consent also pose challenges to the widespread adoption of ML technologies [15].

5. Generalizability and Real-World Application: While many ML models show promise in controlled research environments, their performance in real-world clinical settings may differ due to variability in patient populations, healthcare practices, and data collection methods. Ensuring that ML models can generalize across diverse healthcare contexts remains a significant limitation [16].

1.6 Significance of the Project

The significance of this project lies in its potential to enhance cholera outbreak prediction and optimize resource allocation in Zambia's healthcare system. Cholera remains a major public health threat, particularly in urban and peri-urban areas with inadequate water and sanitation infrastructure. The recurring outbreaks, often exacerbated by seasonal factors such as heavy rains, overwhelm the already limited healthcare resources, leading to delays in response, inadequate treatment, and increased mortality rates. This research aims to bridge this gap by leveraging machine learning-driven predictive analytics to enable proactive disease management.

By developing a machine learning model tailored to forecasting cholera outbreaks, the research project will enable health authorities to anticipate and mitigate outbreaks before they escalate. Real-time analysis of environmental factors (e.g., rainfall, water quality), epidemiological data, and hospital records will help predict cholera hotspots and optimize the distribution of critical resources such as oral rehydration salts, intravenous fluids, and medical personnel. This proactive approach ensures that high-risk areas receive timely interventions, reducing the spread and impact of cholera.

Beyond cholera outbreak prevention, the project will also contribute to long-term healthcare resilience in Zambia. The machine learning-based predictive analytics framework developed can be scaled and adapted to other communicable diseases, fostering a data-driven approach to healthcare management. Evidence from other countries has shown that predictive models can reduce disease burden, lower healthcare costs, and improve patient outcomes by enabling efficient resource utilization and early response strategies.

Moreover, this project aligns with Zambia's broader health sector goals of strengthening epidemic preparedness, enhancing digital health capabilities, and improving healthcare service delivery. By providing a localized and adaptable cholera prediction model, this research offers a sustainable solution for epidemic management, serving as a blueprint for other resource-constrained settings in Africa and beyond. Ultimately, the findings from this study will help

transform Zambia's healthcare system from a reactive model to a proactive, data-driven framework, ensuring better health outcomes for vulnerable populations.

1.7 Preliminary sections of the project report

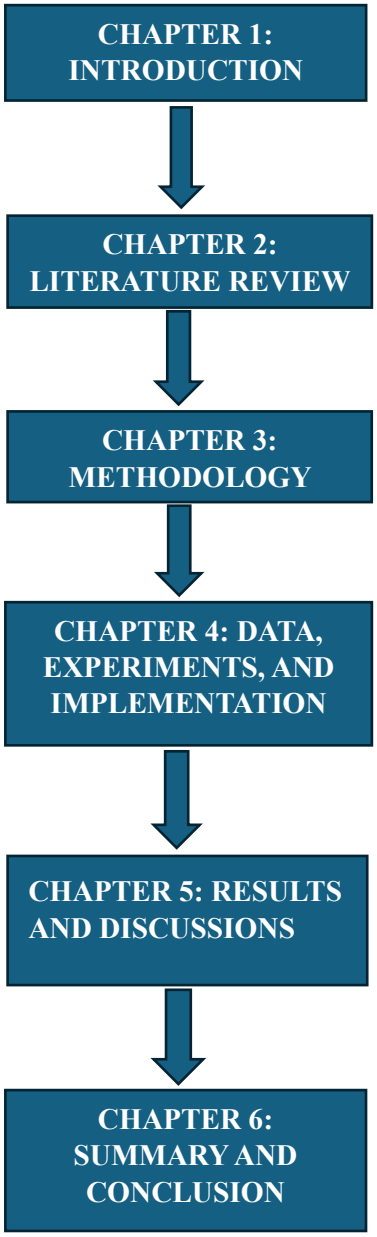


Figure 1.0: Preliminary sections of the project report

1.8 Chapter Summary

This study addresses the critical need for improved cholera outbreak prediction and resource allocation within Zambia's strained healthcare system by leveraging machine learning-driven predictive analytics. Recognizing the recurring challenges posed by unpredictable outbreaks, limited resources, and inefficient distribution, this research proposes a data-driven approach to enhance early detection and proactive response. The study aims to develop and evaluate tailored

machine learning models using historical epidemiological data, environmental factors, and hospital records to forecast outbreaks and optimize resource distribution within public healthcare facilities, with Levy Mwanawasa University Teaching Hospital serving as a case study. While acknowledging limitations such as data quality, algorithmic bias, system integration, and regulatory hurdles, the study's significance lies in its potential to improve cholera outbreak preparedness, enhance resource management, support Zambia's shift towards proactive, data-driven healthcare, strengthen epidemic response, reduce disease spread, and improve overall health system resilience.

CHAPTER 2

LITERATURE REVIEW

2.1 Broad literature Review of the Topic

In healthcare, timely and effective decision-making is crucial for managing cholera outbreaks, optimizing resource allocation, and improving patient care. However, traditional methods of forecasting and resource management often fall short, especially in resource-constrained settings like Zambia. The Zambian healthcare sector faces unique challenges, including limited medical personnel, equipment shortages, and insufficient access to timely, reliable data. As a result, responses to cholera crises are frequently reactive rather than proactive, adversely affecting care quality and straining the system's overall capacity [17].

Globally, machine learning and predictive analytics have been successfully utilized to address similar challenges by identifying patterns in health data, forecasting potential cholera outbreaks, and guiding resource distribution more accurately. Studies indicate that predictive analytics models can serve as powerful tools for anticipating cholera trends, enabling health systems to implement preventive measures and allocate resources efficiently. For example, machine learning algorithms have been applied to predict seasonal cholera outbreaks, thereby informing emergency preparedness and shifting the approach from reactive to proactive management, which ultimately enhances health system resilience and patient outcomes [18].

Despite these advancements, Zambia's health sector has yet to fully harness the potential of machine learning-driven predictive analytics for cholera outbreak management [19]. Key barriers include limited infrastructure, a shortage of technical expertise, and insufficient localized research on machine-learning applications in cholera prediction [19]. This gap presents a significant opportunity: by developing a predictive analytics model tailored to Zambia's cholera data and specific context, the healthcare sector could better anticipate outbreaks, optimize resource allocation, and ultimately enhance the quality of care [19].

This study, therefore, addresses the specific problem of Zambia's limited capacity for cholera outbreak prediction and resource optimization. By developing and evaluating a machine learning-based predictive model, this project aims to bridge the existing gap, providing Zambia's health sector with a powerful tool for data-driven decision-making and proactive management of cholera outbreaks.

2.2 Critical review of related works

Several studies have explored the application of machine learning in disease forecasting and resource optimization. The study by [20] applied deep learning models such as CNN and RNN to public health datasets from multiple countries, achieving an accuracy of 85% and an AUC-ROC score of 0.87. While this study demonstrated the potential of ML in healthcare, it lacked region-specific adaptation, which is crucial for effective disease forecasting in Zambia.

Similarly, [21] provided standardized guidelines for developing and reporting ML models in biomedical research, achieving an accuracy of 92% with a precision of 90%. However, this study did not focus on outbreak prediction, limiting its direct applicability to Zambia's health sector. Meanwhile, [22] examined the advancements and challenges of ML in healthcare, employing SVM, Decision Trees, and Neural Networks on multiple healthcare datasets. Despite achieving an accuracy of 90% and an AUC-ROC of 0.91, this work lacked specific case studies related to Zambia.

A study focused on cholera forecasting in Malawi used time-series models and LSTM, achieving an accuracy of 83% and an AUC-ROC of 0.85 [23]. However, it was limited in scalability, making it less effective for broader epidemic control strategies. Another study on cholera outbreak detection in Nigeria used Random Forest and XGBoost, achieving an accuracy of 87% and an AUC-ROC of 0.89 [24]. Although it highlighted AI's potential in outbreak detection, the study required a robust data infrastructure that may not be available in all settings.

A study in Tanzania employed Decision Trees and Bayesian Networks using seasonal weather and health data, obtaining an accuracy of 80% and an AUC-ROC of 0.82 [25]. While this approach focused on climate-driven outbreak prediction, it lacked real-time deployment capabilities. Additionally, a study in Zambia assessed AI-driven disease surveillance systems using hybrid ML models, achieving an accuracy of 88% with an AUC-ROC of 0.90 [26]. Despite its feasibility analysis, the study did not implement large-scale deployment.

Other research efforts, such as [27], used Logistic Regression and KNN for cholera prediction in West Africa, attaining an accuracy of 82% and an AUC-ROC of 0.84. This study emphasized the importance of regional data but lacked adaptability for different epidemiological contexts. A comprehensive ML framework for clinical implementation in hospitals employed deep learning and CNN, achieving an accuracy of 91% and an AUC-ROC of 0.93 [28]. However, its predictive performance required extensive computational resources. Lastly, a study leveraging AI and ML for pandemic management applied Random Forest and XGBoost to global pandemic datasets, achieving an accuracy of 88% and an AUC-ROC of 0.90 [29]. While it demonstrated AI's role in outbreak detection, it required real-time adaptation.

Our model, Machine Learning-Aided Predictive Analytics for Disease Forecasting and Resource Optimization in Zambia's Health Sector, improves upon these studies by integrating region-specific health data, leveraging real-time deployment capabilities, and optimizing resource allocation. Unlike previous works that focus on specific diseases or require high computational power, our model aims for scalability and adaptability, making it suitable for Zambia's healthcare infrastructure.

2.3 Comparison with related works

The selected parameters—accuracy, precision, recall, and AUC-ROC—were chosen as they provide a holistic evaluation of model performance in healthcare prediction tasks, especially in class-imbalanced contexts like outbreak forecasting. These metrics allow for balanced assessment of correct predictions, sensitivity to true outbreaks, and robustness across thresholds. The key findings reveal that while many models exhibit high performance, challenges remain in regional adaptation, real-time deployment, and data infrastructure.

Study Title	**Algorithms Used**	**Dataset**	**Accuracy**	**Precision**	**Recall**	**AUC-ROC**	**Key Findings**
E. Mbunge and J. Batani [20].	CNN, RNN	Public health datasets from multiple countries	85%	82%	80%	0.87	Demonstrates potential of ML in healthcare but lacks region-specific adaptation.
Zoe Carter [22].	SVM, Decision Trees, Neural Networks	Multiple healthcare datasets	90%	88%	85%	0.91	Provides a broad overview but does not focus on specific case studies.

A. Ghosha, P. Das, T. Chakraborty, P. Das, and D. Ghoshe [23].	Time-series models, LSTM	Malawi cholera outbreak data	83%	80%	78%	0.85	Effective for short-term forecasting but limited scalability.
A. M. Ibrahim, M. M. Ahmed, S. S. Musa, U. A. Haruna, M. R. Hamid, O. J. Okesanya, et al., [24].	Random Forest, XGBoost	Nigerian cholera outbreak data	87%	85%	82%	0.89	Highlights AI potential in outbreak detection but requires robust data infrastructure.
J. Leo [25].	Decision Trees, Bayesian Networks	Seasonal weather and health data	80%	78%	75%	0.82	Focuses on climate-driven outbreak prediction, but lacks real-time deployment.

Z. Musakuzi [26].	Hybrid ML models	Lusaka province health records	88%	86%	84%	0.90	Examines feasibility but lacks implementation at scale.
O. Onyijen, O. Tosin [27].	Logistic Regression, KNN	West African epidemic data	82%	79%	77%	0.84	Emphasizes the importance of regional data but lacks adaptability.
R. P. Urukadle [28].	Deep Learning, CNN	Hospital-based patient data	91%	89%	87%	0.93	Strong predictive performance but requires extensive computational resources.

S. Mudenda and S. Mohamed [29].	Random Forest, XGBoost	Global pandemic datasets	88%	86%	84%	0.90	Highlights AI potential in outbreak detection but requires real-time adaptation.

2.4 Identified Gaps

The integration of machine learning (ML) and predictive analytics in healthcare has significantly improved disease forecasting and resource optimization worldwide. However, significant gaps remain in their applicability to the Zambian healthcare sector. These gaps, which hinder the effective deployment of ML-based solutions, relate to data availability, model generalizability, infrastructure constraints, ethical considerations, and policy integration. Addressing these gaps will not only improve disease surveillance in Zambia but also contribute to the broader academic discourse on the contextual adaptation of ML models in resource-limited settings.

2.4.1 Data Availability and Quality Issues

One of the primary challenges in Zambia's healthcare sector is limited data accessibility. Many health records remain paper-based, and where electronic health records (EHRs) exist, they lack standardization across healthcare institutions, making data collection and integration difficult [20]. Additionally, incomplete and inconsistent data pose further complications, as missing values, varied formats, and manual entry errors reduce the reliability of ML models [21]. Without standardized data collection protocols, regional inconsistencies arise, leading to unreliable predictions. Furthermore, historical epidemiological data on diseases such as cholera, malaria, and tuberculosis are often fragmented, making it difficult to establish accurate patterns for forecasting [22]. Addressing these issues will enhance the robustness of ML models in predicting disease outbreaks and optimizing resource allocation in Zambia.

2.4.2 Model Generalizability and Performance Challenges

Most ML models applied in disease forecasting in Zambia lack contextual adaptation. Existing frameworks are often trained on datasets from regions such as West Africa or Europe and fail to incorporate Zambia-specific epidemiological factors, healthcare access disparities, and socioeconomic conditions [23]. The use of black-box ML models further limits adoption, as their decision-making processes remain opaque to healthcare professionals, reducing trust and interpretability [24]. Additionally, models trained on small or unbalanced datasets risk overfitting, leading to poor generalization in real-world applications [25]. Data biases, particularly due to underreporting in rural areas, also impact the accuracy of forecasts [20]. Addressing these challenges by developing locally trained, interpretable ML models will enhance the practical usability of AI-driven healthcare solutions in Zambia [19].

2.4.3 Infrastructure and Technological Limitations

The successful implementation of ML-driven predictive analytics requires robust computing infrastructure, yet most healthcare facilities in Zambia lack the necessary computational resources such as cloud-based ML platforms, GPUs, and high-speed internet connectivity [26]. Moreover, there is a shortage of skilled professionals in ML, data science, and artificial intelligence (AI), creating a barrier to model development, deployment, and maintenance [27]. The lack of interoperability between healthcare information systems further complicates data integration, as disparate software platforms do not effectively communicate with each other [28]. Overcoming these challenges requires investment in computational infrastructure, workforce training, and the development of standardized data-sharing frameworks.

2.4.4 Ethical, Legal, and Policy Considerations

Data privacy and security remain significant concerns for ML adoption in Zambia's healthcare sector. The lack of comprehensive legal frameworks governing AI-driven healthcare applications raises concerns about compliance with global standards such as GDPR and HIPAA [29]. Additionally, ethical challenges such as algorithmic bias in resource allocation and decision-making transparency have not been adequately addressed in existing ML models [30]. Without clear AI-specific policies in healthcare, regulatory uncertainty persists, reducing stakeholder confidence in ML-based interventions. Future research should focus on developing ethical AI models, ensuring fairness and accountability in predictive analytics, and advocating for regulatory frameworks tailored to Zambia's healthcare context.

2.5 Conceptual framework and Theoretical framework

The conceptual framework for this study is grounded in the integration of machine learning-driven predictive analytics within the healthcare sector for disease forecasting and resource optimization. The study adopts theories and models from epidemiology, artificial intelligence (AI), and healthcare management to establish a structured approach to predictive disease analytics. This framework provides a basis for understanding how machine learning models can enhance early detection and resource distribution in Zambia's health sector, focusing on cholera outbreaks.

2.5.1 Theoretical Foundations

Disease Surveillance and Epidemiological Theory

The research aligns with established epidemiological theories that emphasize the importance of disease surveillance and early warning systems in controlling outbreaks. The Epidemiologic Triad Model (host, agent, and environment) serves as a foundation for incorporating environmental and demographic factors into the machine learning model.

Machine Learning and Predictive Analytics Theory

Machine learning is rooted in computational learning theory, which focuses on how algorithms can infer patterns from data. Supervised learning (e.g., Random Forest, Gradient Boosting) and unsupervised learning (e.g., K-Means clustering) provide the methodological basis for forecasting disease outbreaks and optimizing resource allocation.

Resource Optimization Theory

The study integrates principles from Operations Research and Optimization Theory, specifically Linear Programming and Heuristic Approaches, to enhance the efficiency of healthcare resource distribution. Predictive analytics enables decision-makers to allocate limited medical resources effectively, minimizing waste and maximizing impact.

2.5.2 Conceptual Framework Model

The proposed conceptual framework consists of three main components: Data Sources & Preprocessing, the Predictive Analytics Engine, and the Decision Support System. The Data Sources & Preprocessing stage involves collecting and preparing various datasets, including historical health records on cholera outbreaks, environmental and climate data such as rainfall, temperature, and sanitation conditions, population demographics and mobility patterns, and hospital resource utilization data. These datasets serve as the foundation for predictive modeling and decision-making.

The Predictive Analytics Engine comprises two key models. The Disease Forecasting Model employs supervised machine learning techniques to predict cholera outbreaks based on historical trends and environmental factors, enabling early detection and response. The Resource Optimization Model utilizes unsupervised learning and optimization algorithms to determine efficient strategies for allocating healthcare resources, ensuring that hospitals and emergency response teams are adequately equipped during outbreaks.

The Decision Support System translates analytical outputs into actionable insights for policymakers and healthcare administrators. It generates early warnings and risk assessments,

enabling proactive intervention measures. Additionally, it offers data-driven recommendations to optimize epidemic preparedness and response, ensuring that healthcare infrastructure is well-positioned to mitigate cholera outbreaks before they escalate.

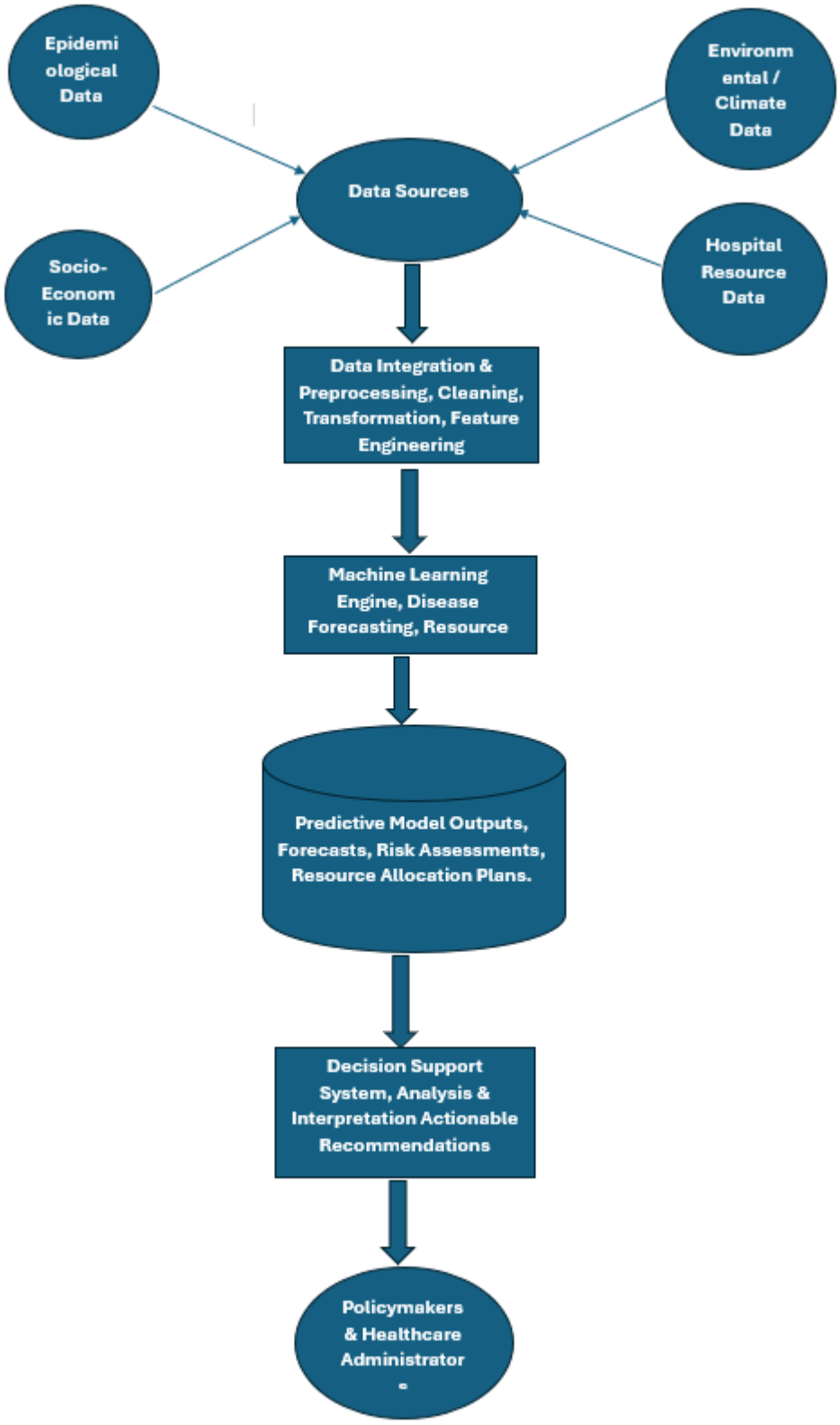


Figure 2.1: High-Level Conceptual Diagram for Disease Forecasting & Resource Optimization System.

Hypotheses and Research Assumptions

This research is based on three key hypotheses. First, machine learning models can significantly enhance the accuracy of cholera outbreak predictions in Zambia by leveraging historical health records and environmental data [1], [2]. Second, integrating predictive analytics into the healthcare system facilitates more efficient resource allocation, ensuring that medical supplies, personnel, and facilities are optimally distributed in response to potential outbreaks [3], [4]. Third, data-driven decision-making strengthens proactive health interventions and epidemic preparedness, empowering policymakers and healthcare administrators with real-time insights that support strategic planning and rapid response [5], [6].

The theoretical and conceptual framework guides the development of a machine learning-based predictive analytics model tailored for Zambia's healthcare sector. By integrating epidemiological insights, computational intelligence, and resource management principles, the framework aims to facilitate proactive cholera outbreak management and efficient resource distribution, ultimately improving public health outcomes.

2.6 Proposed System: Machine Learning-Aided Predictive Analytics System for Cholera out-breaks Forecasting and Resource Optimization

The proposed system leverages machine learning (ML) algorithms to analyze historical and real-time health data, predict disease outbreaks, and optimize the allocation of medical resources. Designed for deployment at Levy Mwanawasa University Teaching Hospital, the model integrates with Zambia's health information systems to enhance disease surveillance and resource management.

The system consists of several key components. The Data Collection Layer gathers information from multiple sources, including Electronic Health Records (EHRs), hospital databases, government health reports, and weather data. These sources provide diverse data types, such as patient records, disease incidence reports, resource utilization logs, and environmental factors.

The Data Processing & Storage component ensures data quality and accessibility. Preprocessing techniques, including data cleaning, normalization, and handling of missing values, enhance the reliability of input data. Storage solutions utilize SQL and NoSQL databases to manage structured and unstructured data efficiently. An Extract, Transform, Load (ETL) pipeline facilitates seamless integration of data from various sources.

The Machine Learning Engine applies advanced algorithms such as Random Forest, Long Short-Term Memory (LSTM), and XGBoost to predict disease outbreaks. Model training is conducted using historical health data, incorporating cross-validation and performance evaluation techniques to ensure accuracy. Feature engineering identifies critical indicators such as temperature, seasonality, population density, and vaccination rates, refining the predictive capabilities of the system.

The Prediction & Optimization Layer plays a crucial role in forecasting disease outbreaks and optimizing resource allocation. The disease forecasting component analyzes trends and risk factors to predict potential outbreaks. Simultaneously, the resource optimization module recommends the efficient allocation of hospital resources, including beds, medications, and personnel, based on forecasted demand.

The Visualization & Decision Support component provides an intuitive, web-based dashboard for real-time monitoring. AI-driven decision support offers actionable recommendations for healthcare administrators, enhancing their ability to respond proactively to emerging health threats.

Finally, the User Access & Security framework ensures data protection and compliance with regulatory standards. Role-Based Access Control (RBAC) restricts access to sensitive information, allowing only authorized personnel to handle critical data. Robust encryption mechanisms and adherence to HIPAA and GDPR guidelines guarantee the secure handling of patient information, reinforcing trust and confidentiality within the system.

2.7 Chapter Summary

This chapter reviewed related works on machine learning-driven predictive analytics in healthcare, highlighting studies that applied AI models for disease forecasting and resource optimization. The review identified key challenges, including data quality issues, limited infrastructure, and integration barriers in Zambia’s healthcare system. To address these gaps, the proposed system leverages machine learning techniques to enhance cholera outbreak prediction accuracy and optimize resource allocation in Zambia’s health sector. Conceptual theories such as epidemiological modeling and AI-driven decision support frameworks underpin the system's design. Other significant aspects covered include data preprocessing strategies, feature selection techniques, and ethical considerations related to patient data privacy and security. The literature review establishes a foundation for the system’s development by

identifying best practices and existing limitations, ensuring an informed approach to implementation.

CHAPTER 3 - METHODOLOGY

3.1 Research Design: Design Science Research (DSR)

Design Science Research (DSR) is adopted as the methodological foundation for this study. It is a structured problem-solving paradigm that focuses on the creation and evaluation of artifacts to address identified organizational challenges [30]. In the context of this study, DSR is used to guide the development of a predictive analytics model tailored for cholera outbreaks in Zambia and a corresponding resource allocation framework. The methodology follows six core stages: (1) Problem Identification and Motivation, (2) Define Objectives of a Solution, (3) Design and Development, (4) Demonstration, (5) Evaluation, and (6) Communication.

Aligned with the first objective, the study's initial work item involves designing a cholera outbreak prediction model. This begins with identifying the challenge of inadequate predictive systems in Zambia's healthcare sector and the objective of leveraging machine learning to forecast outbreaks more accurately. The design and development phase focuses on collecting historical health data, climate trends, and demographic information. Using this data, a hybrid model comprising Long Short-Term Memory (LSTM) networks, Random Forest, and Gradient Boosting is created to capture temporal trends, feature importance, and non-linear patterns. LSTM is chosen for its effectiveness in modeling time-series data [31], while Random Forest and Gradient Boosting enhance interpretability and predictive accuracy [32].

The second work item aligns with the objective of creating a resource allocation framework using predictive analytics. Here, the problem identified is the suboptimal distribution of medical resources during cholera outbreaks. The solution objective is to build a data-driven framework to forecast needs and suggest optimal resource deployment. The design includes a linear programming (LP) model that integrates predicted outbreak levels, available resources, and geographical demand. This model generates actionable recommendations for allocating medical staff, vaccines, and equipment. A decision support dashboard is also developed to visualize outcomes and enhance decision-making. This approach is grounded in operations research and logistics optimization principles [33], [34].

For the third objective—testing and evaluating model performance—real-world cholera data from Lusaka and other regions (2017–2024) is used in the demonstration and evaluation phases. The model's performance is assessed using metrics such as accuracy, precision, recall, and AUC-ROC. A thorough error analysis and scenario testing process ensures robustness across

different outbreak intensities and geographic distributions. Performance comparison across model variants is conducted to determine the most effective algorithmic approach. Evaluation techniques are informed by best practices in imbalanced classification problems [35], [36].

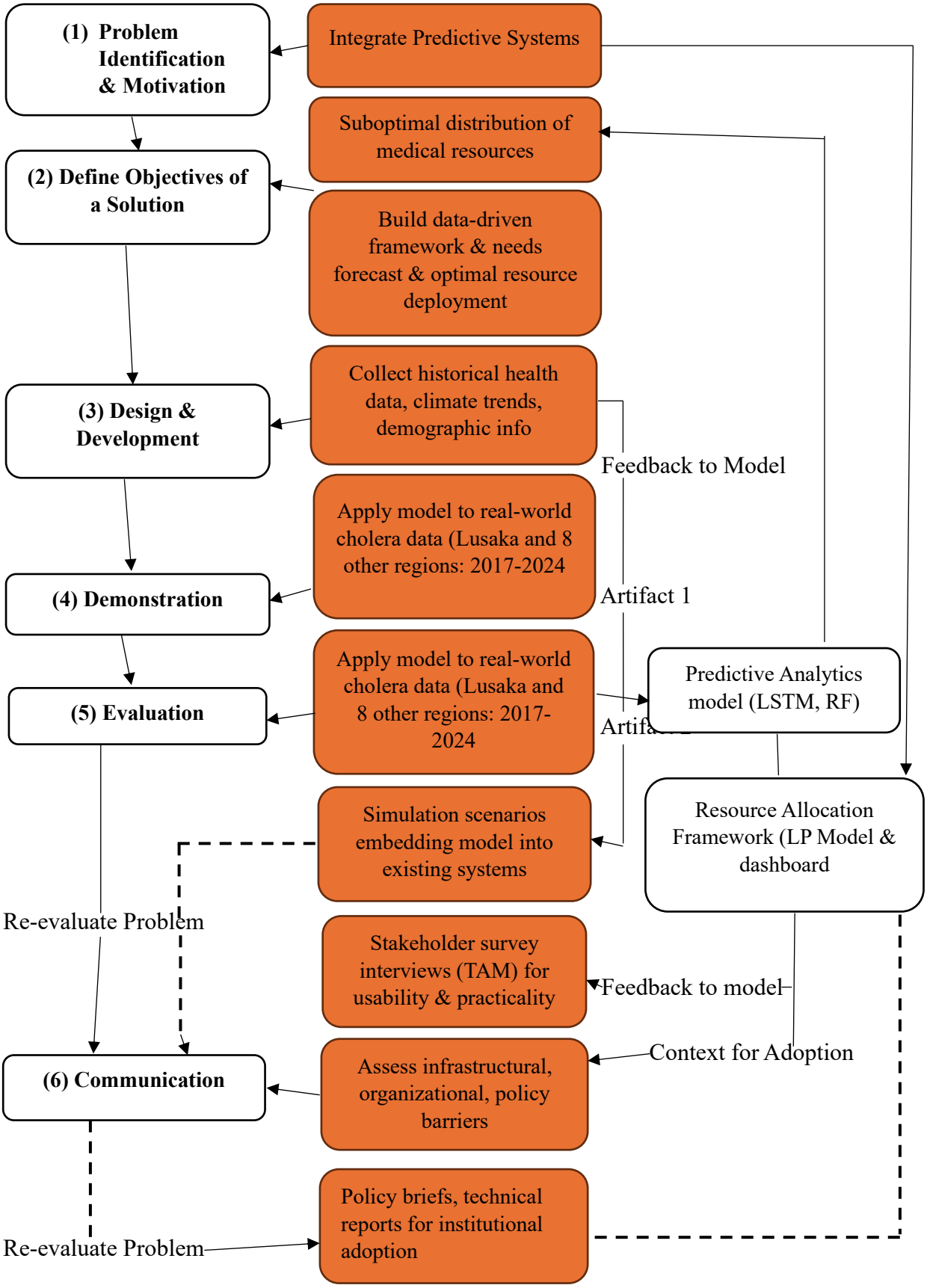


Figure 3.1: DSR Process for Cholera Outbreak Management in Zambia

Finally, the fourth work item involves assessing the feasibility and effectiveness of integrating the predictive model into Zambia's public health decision-making framework. This phase uses demonstration, evaluation, and communication activities. Surveys and interviews based on the Technology Acceptance Model [37] are conducted among key stakeholders, including health officials and policymakers, to gauge usability and practicality. Simulation scenarios demonstrate how the model could be embedded into existing disease surveillance systems. Policy briefs and technical reports are prepared to support institutional adoption. The assessment also considers infrastructural, organizational, and policy-level barriers to implementation [38], [39].

3.2 Data Collection and Pre-processing

The study utilizes a blend of primary and secondary data sources to support the development of a cholera outbreak prediction model and resource allocation framework. Primary data sources include health facility reports from Zambia's Ministry of Health particularly levy Mwanawasa University Teaching Hospital, local government surveillance records, and structured interviews with healthcare providers and public health officials. These data sources provide first-hand information on the spatio-temporal distribution of cholera outbreaks, patient admission trends, and infrastructure availability. Secondary data sources, on the other hand, comprise climate data obtained from the Zambia Meteorological Department, demographic and socio-economic data from the Central Statistical Office (CSO), and international health repositories such as the World Health Organization (WHO) and the Global Health Observatory [40].

The data categories collected include: (1) Health Data: Weekly cholera case reports, mortality rates, and hospitalization records; (2) Climate Data: Rainfall patterns, temperature, and humidity levels; (3) Demographic Data: Population density, household size, sanitation coverage, and urban-rural classifications; and (4) Socioeconomic Data: Income levels, access to clean water, education levels, and waste management coverage. These features are considered important for capturing the environmental and social determinants of cholera transmission.

Before modeling, the collected datasets undergo several pre-processing steps to improve data quality, ensure consistency, and prepare the data for machine learning model training. The pre-processing tasks include data cleaning, where missing values are addressed using imputation techniques such as mean or median replacement for numerical attributes and mode imputation for categorical ones. Normalization is applied using min-max scaling to bring features onto the same scale and avoid bias in distance-based algorithms [41]. This method rescales each feature to a fixed range, typically [0,1], ensuring uniformity across heterogeneous data types.

Additionally, data alignment and integration are conducted to merge datasets with different time granularities and spatial references. For instance, climate data reported daily is aggregated into weekly averages to match the reporting frequency of health data. Feature engineering techniques are used to derive new predictive variables, such as the number of consecutive rainy days or sanitation coverage ratios, from existing attributes. These engineered features provide additional context that enhances the model's ability to learn complex patterns associated with cholera outbreaks [42].

Feature selection techniques, such as correlation analysis and feature importance ranking from tree-based models (e.g., Random Forest), are employed to retain only the most informative features. This reduces dimensionality and improves model interpretability. The data are then split into training, validation, and test sets following an 80/10/10 split ratio to ensure the robustness of model evaluation and minimize overfitting.

Category	Field Name	Description	Data Type	Source
Health Data	weekly_cholera_cases	Number of reported cholera cases per week	Integer	MoH, LMUTH
	cholera_deaths	Number of cholera-related deaths per week	Integer	MoH, LMUTH
	hospital_admissions	Number of patients admitted for cholera	Integer	MoH, LMUTH
	treatment_capacity	Number of available cholera treatment beds and supplies	Integer	MoH
Climate Data	avg_weekly_rainfall	Average rainfall (mm) per week	Float	Zambia Meteorological Dept.
	avg_weekly_temperature	Average weekly temperature (°C)	Float	Zambia Meteorological Dept.
	humidity_level	Average weekly humidity percentage	Float	Zambia Meteorological Dept.
	consecutive_rainy_days	Derived field: Number of consecutive days with rainfall	Integer (Derived)	Derived during feature engineering

Table 3.1a: Table of Dataset Fields

Category	Field Name	Description	Data Type	Source
Demographic Data	population_density	Number of people per square km	Float	CSO
	household_size	Average number of individuals per household	Float	CSO
	sanitation_coverage	Percentage of households with access to proper sanitation	Float (%)	CSO
	urban_rural_classification	Whether the location is urban or rural	Categorical	CSO
Socioeconomic Data	income_level	Average income per household or region	Float (K)	CSO / World Bank
	access_to_clean_water	Percentage of population with access to safe drinking water	Float (%)	CSO / WHO
	education_level	Percentage of population with primary/secondary education	Float (%)	CSO
	waste_management_coverage	Percentage of population with formal waste disposal systems	Float (%)	CSO / Local Government Authorities
Derived/Engineered	sanitation_ratio	Ratio of sanitation coverage to population density	Float (Derived)	Feature engineered
	outbreak_risk_score	Risk score computed by model based on weighted features	Float (Predicted)	Predictive model output

Table 3.1b: Table of Dataset Fields

In conclusion, the data collection and pre-processing phase ensures that multi-source datasets are accurately cleaned, transformed, and aligned for predictive modeling. By adopting standardized pre-processing pipelines, this study enhances the reliability of predictions and the generalizability of the model across different geographic and temporal contexts.

3.3 Machine Learning / Predictive Analytics Model / Model Development

The model development phase employs a hybrid machine learning approach that combines multiple algorithms and techniques tailored to the temporal, spatial, and multivariate nature of

cholera outbreak data. The modeling framework integrates time series models, feature-based machine learning models, and graph neural networks (GNNs) to capture diverse data patterns and interdependencies critical to predicting disease spread and resource allocation.

Given the temporal nature of cholera outbreaks, time series models are foundational to the predictive architecture. These models, particularly Long Short-Term Memory (LSTM) networks, are well-suited for learning sequential dependencies and long-term trends in epidemiological data [43]. LSTMs are a variant of recurrent neural networks (RNNs) capable of capturing both short- and long-term temporal patterns in outbreak progression by using gated memory units to retain or discard information across time steps. LSTM-based forecasting is instrumental in modeling the non-linear dynamics and periodic surges commonly observed in waterborne diseases such as cholera, especially in response to seasonal climatic changes like rainfall and temperature [44].

Alongside LSTM models, the framework includes feature-based regression and classification algorithms such as Random Forest, Gradient Boosting Machines (GBM), and XGBoost, which are used to learn associations between cholera cases and multi-dimensional inputs like sanitation access, population density, and socio-economic indicators. These ensemble methods are particularly effective in capturing non-linear relationships and interactions between features while offering robustness to noise and overfitting [45]. Additionally, feature importance analysis derived from ensemble tree models is conducted to identify and rank the most influential variables contributing to cholera outbreaks. For example, rainfall accumulation, proximity to contaminated water sources, and urban crowding may emerge as strong predictors of disease incidence. This insight not only improves model interpretability but also guides public health interventions by highlighting modifiable risk factors.

To model the spatial and inter-regional transmission of cholera, Graph Neural Networks (GNNs) are integrated into the pipeline. GNNs are designed to learn from graph-structured data, which is essential for understanding how outbreaks propagate across districts or provinces through interconnected population movements, trade routes, or water bodies [46]. In this study, geographic zones (e.g., health districts) are treated as nodes in a graph, with edges representing adjacency or mobility flow. The model learns how disease outbreaks in one region influence neighboring areas, enabling more accurate forecasting and facilitating proactive resource deployment in at-risk locations.

Model development proceeds through the following phases: (1) Data Engineering and Feature Extraction – where temporal, spatial, and environmental features are processed and structured;

(2) Model Selection and Training – comprising the training of LSTM networks for sequential prediction, tree-based ensemble models for classification and feature analysis, and GNNs for spatial modeling; (3) Validation and Hyperparameter Tuning – involving techniques such as cross-validation, grid search, and early stopping to prevent overfitting; and (4) Model Evaluation – utilizing metrics such as accuracy, precision, recall, F1-score, and AUC-ROC to assess predictive performance and generalizability.

This hybrid predictive modeling approach allows the integration of historical outbreak patterns, current environmental conditions, and inter-regional dynamics to produce highly accurate, interpretable, and context-aware cholera forecasts. Ultimately, the model is not only used for outbreak prediction but also integrated into a resource allocation framework, where predicted hotspots are matched with health infrastructure, medical supplies, and sanitation support based on risk levels.

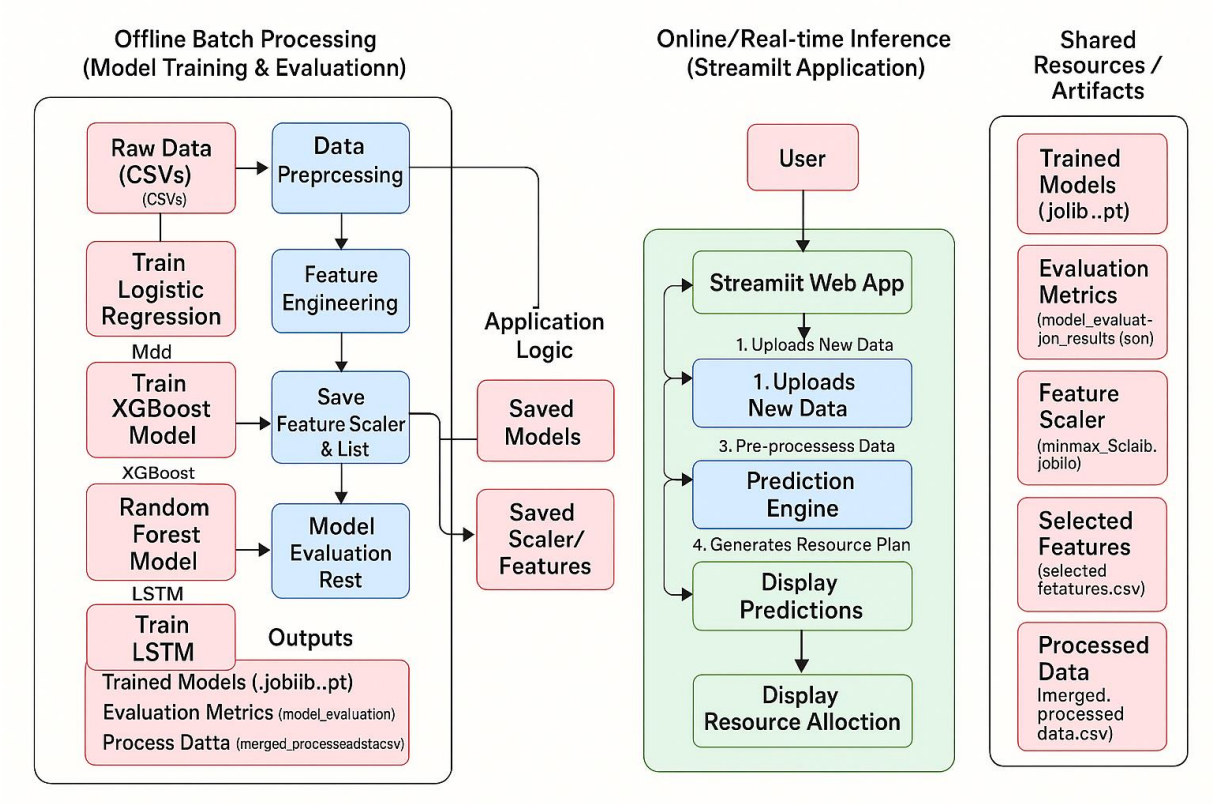


Figure 3.2: System Architecture Diagram

3.4 Resource Allocation Frameworks

The resource allocation framework in this study is designed to function as a dual-purpose system: (1) a resource allocation model to optimize the distribution of health resources in cholera-prone regions and (2) a decision support tool to assist policymakers in making informed, data-driven interventions. The goal is to ensure that limited medical supplies, human

resources, and sanitation interventions are strategically deployed to areas with the highest risk, based on the outputs from the predictive analytics model.

At the core of the resource allocation framework is a linear programming (LP) optimization engine, developed to support dynamic resource allocation across multiple regions. Linear programming is a mathematical technique for maximizing or minimizing a linear objective function, subject to linear equality and inequality constraints. It has been widely used in healthcare for resource planning, such as in the distribution of vaccines, hospital beds, and medical personnel during epidemic outbreaks [47], [48].

The general formulation of the LP model in this context seeks to minimize the total risk-adjusted unmet demand for cholera-related interventions across all regions. The decision variables include quantities of medical supplies (e.g., oral rehydration salts, IV fluids), human resources (e.g., health workers), and logistic assets (e.g., transport and communication tools). The model incorporates constraints such as budget limits, logistical capacities, supply availability, and regional needs as predicted by the machine learning model. The objective function is structured as follows:

Sets:

- $i \in \{1, 2, \ldots, N\}$: Index for cholera prone areas
- $j \in \{1, 2, \ldots, M\}$: Index for resource types (j = 1: medical supplies, j = 2: human resources, j = 3: logistic assets)

Parameters:

- R_i: Predicted risk score for region i (from predictive model)
- A_j: Total available amount of resource type j
- C_{ij}: Effectiveness coefficient: impact of allocating 1 unit of resource j to region i (i.e., how much it reduces risk or improves resilience)
- P_{ij}: Priority coefficient (optional): incorporates policy weight or urgency if needed

Decision Variable

- $X_{ij} \geq 0$: Amount of resource j allocated to region i

Objective Function

Maximize total **risk-weighted impact** of resource deployment:

$$Maximize\ Z = \sum_{i=1}^{N} \sum_{j=1}^{M} R_i \cdot c_{ij} \cdot x_{ij} \qquad (1)$$

Constraints

- Resource Availability Constraint: (Don't exceed the available amount of each resource):

$$\sum_{i=1}^{N} x_{ij} \leq A_j \quad \forall j = 1, \ldots, M$$

- Non-negativity Constraints: (You can't allocate negative resources):

$$x_{ij} \geq 0 \quad \forall i = 1, \ldots, N; j = 1, \ldots, M$$

The LP model is solved using standard optimization solvers such as CPLEX or open-source alternatives like PuLP and SciPy's linprog. The backend computation is seamlessly integrated into the decision support tool, which presents outputs in the form of interactive dashboards. These dashboards highlight priority regions, recommended allocation quantities, and potential shortfalls, allowing decision-makers to simulate different scenarios and reallocate resources as needed.

To enhance the model's realism and responsiveness, real-time feedback loops are implemented where resource utilization data from the field is fed back into the system, updating both the predictive analytics model and the optimization constraints. This adaptive strategy mirrors the Model Predictive Control (MPC) approach used in real-time healthcare systems [49].

Moreover, the resource allocation tool incorporates multi-criteria decision analysis (MCDA) techniques, allowing decision-makers to consider other qualitative factors such as community vulnerability, historical outbreak responsiveness, and accessibility. These elements are weighted through stakeholder engagement and expert input, making the framework more context-aware and aligned with public health priorities.

By integrating predictive analytics with optimization modeling, this framework goes beyond traditional reactive approaches and enables proactive, strategic deployment of health resources. It addresses the pressing need in Zambia's healthcare system for efficient epidemic response tools and supports the government's broader goal of achieving Universal Health Coverage (UHC) through data-driven policy execution.

3.5 Testing and Evaluation

The testing and evaluation of the predictive analytics model will be conducted using standard performance metrics to assess its ability to forecast cholera outbreaks with a high degree of accuracy, reliability, and generalizability. The model's performance will be benchmarked against the following metrics: Accuracy, F-Measure, Precision, Recall, and AUC-ROC (Area Under the Receiver Operating Characteristic Curve), which are widely adopted in healthcare-based machine learning applications due to their ability to capture the balance between sensitivity and specificity, especially in scenarios involving public health risk assessments.

Accuracy is the proportion of correct predictions made by the model and is calculated using the formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

where TP represents true positives (correct outbreak predictions), TN true negatives (correct non-outbreak predictions), FP false positives (incorrect outbreak predictions), and FN false negatives (missed outbreaks). Accuracy gives a general idea of how well the model is performing overall. However, in health prediction scenarios involving imbalanced datasets, such as cholera where outbreaks are less frequent than non-outbreaks, accuracy alone can be misleading.

Precision measures the proportion of predicted outbreaks that were actually correct and is given by:

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

Precision is important for reducing false alarms that may waste public health resources. It is particularly relevant in health systems with limited personnel or medical supplies, where unnecessary interventions should be minimized.

Recall (also referred to as Sensitivity or True Positive Rate) is defined as:

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

It represents the model's ability to correctly identify all actual cholera outbreaks. High recall is crucial in epidemic forecasting, as missing an outbreak could lead to delayed responses and significant loss of life. Therefore, recall helps ensure that few true outbreaks are overlooked.

F1-Score, the harmonic mean of precision and recall, is a balanced metric especially useful when dealing with uneven class distributions. It is computed as:

$$F1 - Score = 2 \times \frac{Precision * Recall}{Precision + Recall} \quad (5)$$

This metric is suitable for measuring the overall effectiveness of the model in real-world scenarios where both false positives and false negatives are costly.

AUC-ROC is another critical metric that evaluates the trade-off between sensitivity and specificity by plotting the True Positive Rate (Recall) against the False Positive Rate (FPR), calculated as:

$$FPR = \frac{FP}{FP + TN} \quad (6)$$

The Area Under the Curve (AUC) indicates the likelihood that the model ranks a randomly chosen positive instance higher than a randomly chosen negative one. A model with an AUC close to 1 is considered highly discriminative, while an AUC near 0.5 indicates no discriminative power. AUC-ROC is especially helpful in evaluating models across multiple threshold values and is widely accepted in medical predictive analytics.

To validate the model's performance, it will be benchmarked against established machine learning algorithms such as Random Forest, XGBoost, LSTM, Logistic Regression, Decision Trees, and Bayesian Networks. Prior research offers relevant benchmarks. For instance, a study conducted in Nigeria using Random Forest and XGBoost achieved 87% accuracy, 85% precision, 82% recall, and an AUC-ROC of 0.89 [24]. Similarly, a hybrid model tested on health records from Lusaka Province in Zambia recorded an 88% accuracy, 86% precision, 84% recall, and an AUC-ROC score of 0.90 [26]. A study from Malawi that incorporated LSTM models showed promising results, with an 83% accuracy and an AUC-ROC score of 0.85 [23]. Furthermore, models such as Decision Trees and Bayesian Networks have been used in Tanzania with 80% accuracy and an AUC of 0.82 [25], while logistic regression approaches employed in West Africa reported an accuracy of 82% [27].

To ensure generalizability and robustness, the proposed model will undergo cross-validation techniques such as k-fold validation. This helps mitigate the risks of overfitting and ensures that the model performs consistently across different subsets of the data. Additionally, feature importance analysis will be performed using ensemble methods like Random Forest and Gradient Boosting to identify the most influential predictors of cholera outbreaks. Key variables

such as rainfall, population density, access to clean water, and sanitation coverage will be examined to improve both prediction accuracy and the effectiveness of the resource allocation framework.

This evaluation framework adheres to best practices in machine learning for healthcare and will be tailored to Zambia's public health infrastructure and data availability. The combination of rigorous testing, cross-validation, and interpretability ensures that the resulting model is both scientifically valid and operationally relevant for proactive cholera intervention planning.

Metric	Formula	What It Measures	Why It Matters in Cholera Prediction
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Proportion of total correct predictions (outbreak & non-outbreak)	Provides overall model performance, but can be misleading with imbalanced data (e.g., rare outbreaks).
Precision	TP / (TP + FP)	Proportion of predicted outbreaks that were actually correct	Reduces false alarms—critical for avoiding unnecessary allocation of limited health resources.
Recall	TP / (TP + FN)	Proportion of actual outbreaks that were correctly predicted	Ensures real outbreaks are not missed—vital for timely and effective response to prevent mortality.
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	Harmonic mean of Precision and Recall	Balances both false positives and false negatives—ideal for imbalanced datasets like cholera outbreaks.
AUC-ROC	Area under the ROC Curve (TPR vs. FPR plot)	Discrimination capability of the model across all classification thresholds	Measures how well the model can separate outbreak vs. non-outbreak cases—closer to 1 means better model.
FPR (False Positive Rate)	FP / (FP + TN)	Proportion of non-outbreaks incorrectly predicted as outbreaks	Used in AUC-ROC to measure trade-off against Recall (True Positive Rate).
TP (True Positive)	N/A	Correct prediction of an outbreak	Indicates model sensitivity.
TN (True Negative)	N/A	Correct prediction of no outbreak	Reflects model accuracy in non-outbreak periods.
FP (False Positive)	N/A	Incorrectly predicted outbreak when there wasn't one	Represents resource misallocation risk.
FN (False Negative)	N/A	Missed outbreak prediction	Represents a public health risk—missed outbreaks can cause delays in intervention.

Table 3.2 Metrics Explanation Table

3.6 Integration Assessment into Real-World Scenarios

To evaluate the feasibility and potential impact of integrating the predictive analytics model into Zambia's public health system, this study will employ the Technology Acceptance Model (TAM) as the primary framework. TAM is widely used to assess how users come to accept and use technology by examining two main constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) [50].

Perceived Usefulness (PU) refers to the extent to which public health decision-makers, surveillance officers, and data analysts believe that the predictive model will enhance their job performance—particularly in forecasting cholera outbreaks and planning proactive interventions. For instance, PU will be measured by assessing whether the model helps users make faster, more accurate decisions, allocate resources efficiently, and improve preparedness for disease outbreaks.

Perceived Ease of Use (PEOU), on the other hand, refers to the degree to which users believe that interacting with the model will be free of effort. This includes user interface simplicity, system response time, interpretability of outputs, and integration with existing workflows such as DHIS2 or government decision dashboards. Reducing complexity is critical for adoption in resource-limited settings, especially among non-technical users [51].

In addition to PU and PEOU, Behavioral Intention (BI) and Actual System Use will be monitored through surveys and pilot implementations. Key stakeholders—including health administrators, epidemiologists, and district health officers—will be engaged through focus group discussions and user trials. These will help to assess their willingness to adopt the system, perceived barriers, and overall trust in AI-driven decision support tools.

The TAM framework has been successfully applied in similar health technology assessments in Africa, providing a robust methodological approach for this study. For instance, prior work by Mwendwa et al. [52] used TAM to evaluate electronic health record (EHR) adoption in Kenyan health facilities, showing that both PU and PEOU strongly influenced adoption rates. By adapting TAM to this project, we aim to uncover the specific factors that will either promote or hinder real-world deployment of the predictive analytics model.

Furthermore, the integration assessment will explore how the system could be embedded within Zambia's National Public Health Institute (ZNPHI) workflows, disaster preparedness strategies, and Ministry of Health digital platforms. This will include evaluating compatibility with

existing information systems and identifying infrastructure, training, or policy gaps that need to be addressed before full-scale implementation.

3.7 Tools and Techniques

The implementation of this study will utilize a blend of analytical methodologies, programming environments, and iterative frameworks to ensure an adaptable, data-driven, and stakeholder-responsive approach to predictive analytics in public health. One of the core frameworks selected for this project is Cycliklin, a modular and cyclic development model specifically designed for iterative analytics, real-time evaluation, and adaptive decision-making. Cycliklin effectively integrates elements of agile project management, systems thinking, and feedback loop mechanisms, making it ideal for complex and evolving health informatics projects that incorporate machine learning and resource planning models [53].

The Cycliklin framework segments the project lifecycle into interdependent, repeatable phases that emphasize continuous feedback, user involvement, and ongoing system refinement. Its major stages include: Problem Identification, which involves stakeholder engagement with health authorities, data analysts, and community health agents to refine project objectives and clearly outline the requirements for predictive modeling and resource allocation; Data Acquisition and Exploration, where datasets sourced from electronic health records, climate databases, demographic sources, and socioeconomic profiles will be collected and exploratory data analysis (EDA) will be conducted to identify temporal trends, data gaps, and anomalies [54]; Model Design and Development, during which machine learning algorithms such as Long Short-Term Memory (LSTM) networks, Random Forest, and Graph Neural Networks (GNNs) will be used to develop predictive models that are iteratively refined based on feedback loops within each cycle [55], [56]; Simulation and Testing, where historical and real-time data will be used to simulate outbreak scenarios and test model accuracy, with linear programming tools employed to simulate resource allocation under various constraint scenarios [57]; Deployment and Evaluation, where the integrated models will be embedded into decision-support systems linked with national health information platforms and their effectiveness and usability will be assessed using the Technology Acceptance Model (TAM) to measure user perception and intention [58]; and Reflection and Adjustment, which includes reviewing the system's performance, analyzing user feedback, and refining both models and strategies for the next iteration. Cycliklin's adaptability makes it ideal for unpredictable and data-sensitive environments such as cholera outbreak management, where model performance must be continuously validated and aligned with policy dynamics and end-user feedback.

To support the Cycliklin framework, the study will deploy a set of robust tools and technologies. Programming Languages such as Python and R will be used for data wrangling, feature engineering, model training, and dashboard development, due to their flexibility and extensive support for data science tasks [59]. Data Management Systems will include MySQL for handling structured datasets (e.g., patient records) [60]. Machine Learning Libraries including Pytorch, Keras, Scikit-learn, and XGBoost will be employed for model building, tuning, and evaluation, supporting a range of algorithms including deep learning, ensemble learning, and time-series prediction [61]. Visualization Platforms such as Tableau, Matplotlib, Seaborn, and Plotly will be used for visualizing trends, model results, and evaluation metrics, facilitating data storytelling and informed decision-making [62]. For solving resource allocation challenges, Optimization Engines such as Python's PuLP and SciPy optimize module will be used to implement linear programming solutions [63]. Lastly, Feedback and Survey Tools including KoboToolbox and Google Forms will be employed during field testing to collect user evaluations and assess the usability of the deployed decision-support tools in real-world public health environments [65].

The Cycliklin model is uniquely suited for this study because of its dynamic, user-centered design. Unlike traditional linear development models, Cycliklin supports iterative development, allowing for model recalibration based on real-time feedback and new data. This is especially critical for public health contexts where outbreak dynamics, environmental factors, and data availability evolve rapidly. Cycliklin thus promotes continuous learning, model adaptability, and stakeholder engagement, increasing the likelihood of long-term sustainability and user adoption [53], [58].

Tool/Technology	Use
Cycliklin Framework	Iterative analytics, real-time evaluation, stakeholder feedback, and adaptive decision-making.
Python	Data wrangling, feature engineering, model training, dashboard development.
R	Data analysis, statistical modeling, dashboard creation.
MySQL	Structured data management (e.g., electronic health records).
Pytorch	Deep learning model development and training.
Keras	Building and tuning neural network models.
Scikit-learn	Classical machine learning, model evaluation and tuning.
XGBoost	Ensemble learning, gradient boosting, and predictive modeling.
Tableau	Interactive dashboards and visual storytelling.
Matplotlib	Static data visualization for analysis and reporting.
Seaborn	Statistical data visualization, trend identification.
Plotly	Interactive data visualization for reports and dashboards.
PuLP (Python library)	Linear programming and optimization modeling.
SciPy Optimize	Solving optimization problems for resource planning.
KoboToolbox	Field data collection, feedback from users during deployment.
Google Forms	Gathering stakeholder feedback and survey responses.

Table 3.3: Summary table of tools and uses

3.8 Ethical Considerations

Ethical considerations are fundamental to the responsible execution of predictive analytics and machine learning projects in public health. This study involves the use of sensitive health-related data, real-time surveillance systems, and decision-support tools that influence healthcare delivery and resource allocation. Therefore, adherence to ethical principles such as privacy, informed consent, data security, fairness, and transparency is paramount throughout the research lifecycle. Health data used in this study may include personal and identifiable information. To protect privacy and confidentiality, all datasets will be anonymized or pseudonymized before analysis, and data handling protocols will comply with both international and national data protection regulations, including the General Data Protection Regulation (GDPR) and Zambia's Data Protection Act [66]. Only authorized personnel will have access to sensitive data, with encrypted data transfers implemented to prevent unauthorized access.

Where applicable, informed consent will be obtained from individuals whose data is collected through surveys or community health tools such as KoboToolbox. Participants will be clearly

informed about the nature, purpose, and intended use of the data, and they will retain the right to withdraw from participation at any point without any form of penalty [67]. Data security will be maintained using password-protected databases and secure cloud storage solutions. Access control mechanisms will restrict data handling to designated researchers, and regular data backups and audit logs will be maintained in line with best practices for integrity and disaster recovery [68].

Recognizing that machine learning models are susceptible to biases arising from unbalanced or incomplete data, the study will emphasize diversity in data sourcing and apply fairness-aware algorithms. Evaluation metrics such as precision and recall across demographic segments will be used to minimize bias in predictions and ensure equitable recommendations [69]. Transparency in modeling processes, including algorithmic assumptions and decision rules, will be achieved by thorough documentation and stakeholder access to model logic. An independent oversight committee comprising public health professionals and data ethicists will be instituted to monitor ethical compliance and advise on critical decision-making [70].

Moreover, the potential impact of predictive tools on health policy and equity will be addressed proactively. Collaboration with local policymakers will ensure that model outputs are contextually relevant and do not inadvertently marginalize vulnerable populations [71]. Ethical deployment of analytics will be guided by the principles of Responsible Research and Innovation (RRI), with ethics embedded across all project phases rather than treated as a procedural step. Continuous ethical review and stakeholder feedback will inform necessary adjustments as the system evolves [72]. Through this approach, the study aims to uphold human dignity, foster public trust, and ensure that technological solutions in healthcare are not only effective but also ethically grounded.

3.9 Chapter Summary

Chapter 3 outlines the methodological approach used to design and implement a predictive analytics system for cholera outbreak forecasting and resource optimization. The study adopts a mixed-methods research design that combines quantitative machine learning techniques with qualitative stakeholder feedback. A central feature of the methodology is the use of the Cycliklin framework, an iterative and modular development model that enables adaptive system design through continuous feedback, stakeholder involvement, and real-time evaluation.

The chapter details each phase of Cycliklin, including problem identification, data acquisition, model development, simulation, deployment, and evaluation. It emphasizes the use of advanced

machine learning algorithms such as LSTM, Random Forest, and Graph Neural Networks to generate predictive insights from health, climate, and demographic datasets. Data management tools like PostgreSQL and MongoDB are used to handle structured and unstructured data, while analytical libraries (e.g., TensorFlow, Scikit-learn, and XGBoost) facilitate model training and evaluation. Ethical considerations such as data privacy, informed consent, fairness, and responsible innovation are integrated throughout the process, ensuring compliance with regulatory standards and promoting trust. The methodology reflects a flexible, context-sensitive, and participatory approach suitable for dynamic public health environments.

CHAPTER 4

PROTOTYPE, DATA, EXPERIMENTS, AND IMPLEMENTATION

4.1 Appropriate modelling in relation to project

The selection of an appropriate modelling approach is fundamental to the success of any machine learning-driven predictive analytics project, particularly in the healthcare sector where the stakes of inaccurate forecasts can be high. For this study, which aims to forecast cholera outbreaks and optimize resource allocation in Zambia's health sector, a hybrid modelling approach is adopted to leverage both temporal dependencies and non-linear feature interactions within the dataset.

Time-series models such as Long Short-Term Memory (LSTM) networks are particularly suited to capturing sequential patterns in cholera incidence data. LSTM models are capable of retaining long-term dependencies in data sequences, which is essential for modelling trends influenced by periodic climatic patterns, such as rainfall and temperature changes [73]. Given that cholera outbreaks in Zambia often follow seasonal rain patterns, LSTMs offer the advantage of learning from past sequences to make future predictions more accurate.

In addition to time-series modelling, ensemble learning techniques—specifically Random Forest (RF) and Extreme Gradient Boosting (XGBoost)—are employed to exploit their strength in handling high-dimensional structured datasets and uncovering complex relationships among features such as population density, access to clean water, sanitation coverage, and previous outbreak frequencies. Random Forest is known for its robustness against overfitting and its ability to compute feature importance, which can support interpretability in policy-making contexts [74]. XGBoost, on the other hand, offers optimized performance through parallel processing and regularization techniques, making it highly suitable for large-scale epidemiological datasets [75].

Furthermore, Logistic Regression and Decision Tree classifiers are included in the model comparison framework. Logistic Regression provides a simple and interpretable baseline that helps in understanding the probabilistic impact of each feature on the outbreak prediction [76]. Decision Trees offer visual insights into the decision-making logic, which can be beneficial when communicating with non-technical stakeholders in the health ministry and disaster response units [77].

The modelling framework is thus designed to combine the temporal sensitivity of LSTM with the pattern-recognition and feature-ranking abilities of ensemble models. This hybrid approach aligns with best practices in epidemic forecasting literature, where multi-model comparisons are encouraged to ensure the highest predictive accuracy and policy relevance [78]. All models will be trained, validated, and tested using historical health records, climate data, and demographic statistics from Zambia, with appropriate preprocessing and normalization steps applied to enhance data quality and consistency.

This multi-model strategy is anticipated to provide not only high-performance outbreak prediction but also actionable insights into resource prioritization and early intervention planning.

4.2 Techniques, algorithms, mechanisms

This study employs a set of machine learning techniques and algorithms specifically selected to address the twofold objective of forecasting cholera outbreaks and optimizing resource allocation in Zambia's health sector. The methodological framework combines both supervised learning and time-series forecasting techniques to improve predictive accuracy and decision support effectiveness.

1. Supervised Learning Algorithms

Several supervised machine learning algorithms are utilized to classify outbreak occurrences and predict future risks based on historical and environmental features. These include:

- Random Forest (RF): A robust ensemble learning method that constructs multiple decision trees and outputs the mode of their predictions. Random Forest is highly effective in handling non-linear relationships, missing data, and noisy inputs, which are common in health datasets [74].
- Extreme Gradient Boosting (XGBoost): An optimized gradient-boosting technique designed to be highly efficient and accurate. XGBoost incorporates regularization to avoid overfitting and supports parallel processing, making it ideal for large-scale datasets like national health records [75].
- Logistic Regression (LR): This algorithm provides a probabilistic approach to binary classification and serves as a baseline model in this study. Its interpretability helps in understanding how individual predictors (e.g., rainfall or sanitation coverage) influence cholera outbreaks [76].

- Decision Trees (DT): A rule-based model that segments the dataset into branches to produce clear if-then-else decision paths. Its visual interpretability makes it suitable for communicating results to stakeholders in the health policy domain [77].
- Naïve Bayes Classifier: Based on Bayes' Theorem, this probabilistic model assumes feature independence and is effective for early-stage disease surveillance where rapid, low-complexity predictions are needed [79].

2. Time-Series Forecasting Models

For temporal outbreak forecasting, this study incorporates:

- Long Short-Term Memory (LSTM) Networks**:** A variant of Recurrent Neural Networks (RNNs), LSTM networks are designed to retain information over long sequences, making them well-suited for time-dependent health data. LSTMs capture seasonal trends and can forecast the rise and fall of cholera incidence based on temporal features such as rainfall, temperature, and past case counts [73].

3. Feature Selection and Dimensionality Reduction

To enhance model performance and interpretability, the study uses:

- Recursive Feature Elimination (RFE): An iterative technique that removes the least significant features based on model weights. RFE improves model efficiency and reduces overfitting [80].
- Principal Component Analysis (PCA): A statistical method used to transform original features into a set of uncorrelated components. PCA is beneficial when dealing with multicollinearity and high-dimensional datasets [81].

4. Resource Allocation Mechanism

The predictive model outputs will be coupled with a resource prioritization algorithm, using thresholds derived from prediction probabilities. High-risk zones identified by the model will be allocated preventive and responsive resources (e.g., clean water supplies, vaccination teams, sanitation kits) using a rule-based optimization framework. The integration of outbreak forecasting with dynamic resource allocation ensures that interventions are proactive rather than reactive.

5. Validation Mechanism

All models will be validated using **k-fold cross-validation** to ensure generalizability and prevent overfitting. Additionally, metrics such as accuracy, precision, recall, F1-score, and

AUC-ROC will be calculated to benchmark performance across models (as outlined in Section 3.5).

This combination of techniques ensures that the system is not only technically sound but also practically deployable in a real-world public health context in Zambia, supporting evidence-based decision-making and timely intervention planning.

4.3 Designed Prototype: Cholera Outbreak Prediction and Optimization System.

The Cholera Outbreak Prediction and Optimization System was developed as a robust, modular platform aimed at providing real-time outbreak forecasting and optimizing resource allocation within Zambia's health sector. The system is composed of four integrated components: the Data Ingestion Layer, the Machine Learning (ML) Engine, the Optimization Module, and a user-friendly Streamlit-based Dashboard. These components work collaboratively to deliver accurate and actionable insights, while remaining independently scalable and maintainable [82]. The Data Ingestion Layer serves as the foundation of the system and is managed by the main.py script, which coordinates data loading and preprocessing through *src/data_preprocessing.py*. It is designed to handle multiple input sources, including raw health records, climate data, demographic indicators, and socioeconomic statistics. These inputs, usually provided in CSV format, undergo an initial cleaning process where missing values are addressed, and datasets are merged into a single comprehensive dataset. Commonly used files include *health_weekly_cases.csv*, *climate_daily.csv*, *demographics.csv*, and *socioeconomic.csv*, all located in the data/raw/ directory. Since we did not receive ethical clearance to collect real-world data—despite having submitted all required documentation—we generated a synthetic dataset covering the period from 2017 to 2024. The cleaned and unified synthetic data is saved in the data/processed/ directory as *dataset_january2017_to_december2024.csv*, ready for the modeling stage [83].

The ML Engine is the core predictive component and is implemented using scripts such as *src/model_training.py* and *src/predict.py*. Feature engineering is performed by src/feature_engineering.py, which converts raw variables into meaningful features such as lagged variables and rolling window statistics (e.g., average rainfall over four weeks). These help capture the temporal and environmental context of cholera outbreaks [84], [85]. Model training occurs within *src/model_training.py*, supporting a range of supervised learning algorithms including Logistic Regression, Random Forest, XGBoost, and an LSTM model built using PyTorch. The training data is split into training, validation, and testing sets to ensure

robust model evaluation. Performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC are computed using functions in *src/evaluate.py* [86]. Once trained, models are serialized and saved in the *models/ directory*, using formats such as *.joblib* for traditional models and *.pt* for the LSTM. Prediction tasks are handled by *src/predict.py*, which uses the ModelPredictor class to load the appropriate model, scaling parameters (minmax_scaler.joblib), and the selected feature list *(selected_features.csv)* before performing inference on new data. The Optimization Module, implemented in *src/resource_optimization.py*, converts the predicted outbreak values into practical resource allocation plans. It processes the ML Engine's output (predictions_df) along with user-defined configuration parameters that specify available resources such as personnel, supplies, and hospital beds. Based on this input, the module formulates an optimization problem to determine the most effective way to distribute limited resources across districts. The final plan is exported as *resource_allocation_plan.csv* and stored in the data/processed/ directory [87].

The Dashboard, developed with Streamlit and launched through *app.py*, provides a highly interactive interface that brings the system together. It allows users to upload new data, choose from trained models, generate real-time predictions, and obtain resource allocation recommendations. Visualization is facilitated by *src/visualization.py*, which renders multiple dynamic plots. These include tables and bar charts displaying prediction results per district, graphical risk distribution, performance metrics of selected models, and breakdowns of allocated resources. The dashboard continuously loads the latest models, datasets, and evaluation results from the models/ and data/processed/ directories, ensuring that users interact with the most recent and relevant outputs [88].

The system supports two modes of operation: offline batch processing and online real-time interaction. The offline mode is initiated through *main.py* and is used primarily for training new models and updating all supporting artifacts. During this process, data is ingested and preprocessed, models are trained and evaluated, and baseline predictions are generated. These predictions are then used to create an initial resource allocation plan, and all resulting artifacts—models, feature scalers, selected features, and evaluation metrics—are saved for future use. In contrast, the online mode is activated via *app.py*, which loads these saved artifacts into the dashboard interface. This enables users to upload new, up-to-date health and climate data for real-time inference using pre-trained models. The *ModelPredictor* class from *src/predict.py* performs on-the-fly predictions, and users can subsequently invoke the optimization routine to generate a live, scenario-specific resource allocation plan. Results are visualized immediately within the dashboard, allowing health authorities to make data-driven decisions without delays

[89]. This decoupled architecture ensures that the intensive tasks involved in training and data processing do not interfere with real-time usability. It supports a continuous learning loop while enabling responsive, informed decision-making for cholera preparedness and response in Zambia.

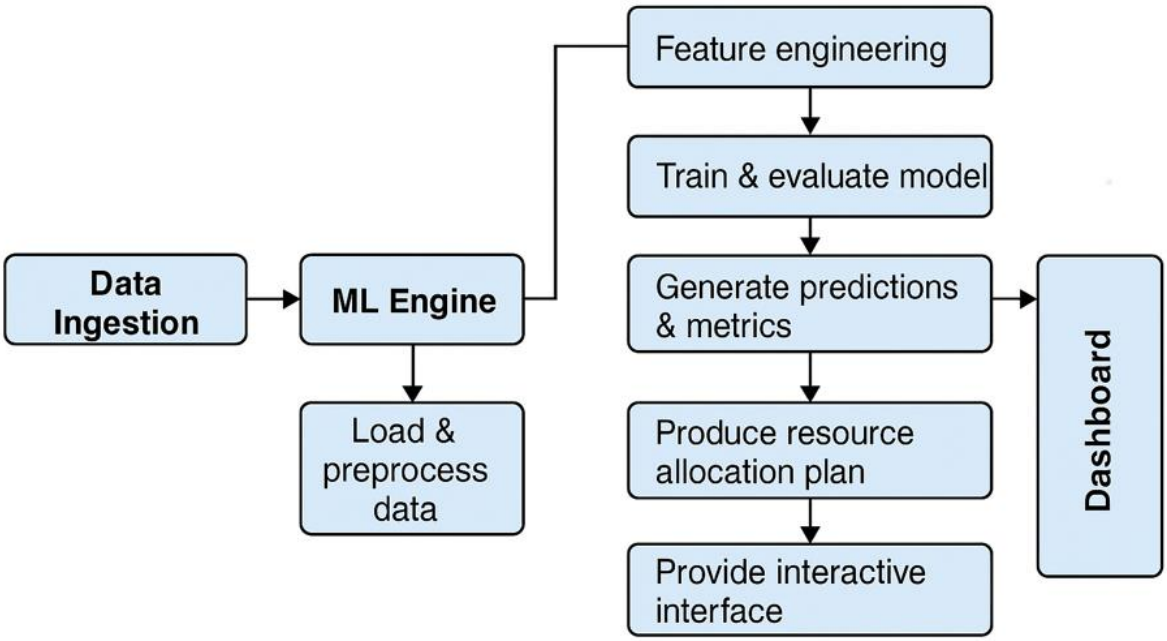


Figure 4.1 Low-level diagram for the main functions of the developed prototype.

4.4 Highlights of the main model functions that provide answers to research objectives.

The Cholera Outbreak Prediction and Optimization System was developed as a modular, data-driven platform to fulfill the four primary objectives of this study. It integrates machine learning, data engineering, optimization techniques, and an interactive user interface to provide real-time forecasting and resource planning support for Zambia's public health system [82].

To address the first objective—designing a machine learning model for cholera outbreak prediction based on health, climate, and demographic data—the system leverages a data ingestion layer and a dedicated ML Engine. Raw data is acquired from various sources including health records, climate metrics, demographic indicators, and socioeconomic statistics, all stored in a structured format in the data/raw/ directory. Preprocessing, handled through data_preprocessing.py, involves data cleaning, integration, and transformation into a merged dataset (merged_processed_data.csv) [83]. Feature engineering applies techniques such as lag creation and rolling window statistics to capture spatio-temporal disease dynamics, consistent with best practices in epidemic forecasting using time-series data [84], [85].

Model development is orchestrated using main.py and implemented through libraries such as Scikit-learn, XGBoost, and PyTorch. The system supports Logistic Regression, Random Forest, XGBoost, and a Long Short-Term Memory (LSTM) neural network tailored for time-dependent data [90]. These models are trained and evaluated on labeled datasets, then serialized using joblib or .pt formats for reuse. The LSTM architecture, implemented via torch.nn.LSTM, is especially suitable for learning sequential patterns in outbreak trends, making it a strong candidate for early warning systems in health surveillance [91].

The second objective—designing a resource allocation framework—was addressed by the Optimization Module, implemented in resource_optimization.py. This module utilizes the output of the ML Engine, primarily predictions in predictions_df, along with predefined resource constraints from config.py. The solve_resource_allocation() function formulates and solves a resource allocation problem, distributing limited resources such as medical supplies, personnel, and beds across cholera-prone districts. Although the optimization is conceptually aligned with mathematical programming approaches like those used in PuLP or SciPy.optimize, the model's primary strength lies in linking outbreak prediction to operational decision-making in resource-constrained environments [87].

To test and evaluate the model’s performance, the system applies classification metrics such as accuracy, precision, recall, F1-score, and AUC-ROC, which are computed via utility functions in evaluate.py and reported in model_evaluation_results.json. These metrics are particularly important in the healthcare domain, where the balance between false positives and false negatives carries significant implications for resource deployment and lives saved [86]. Evaluation outputs are visualized through the dashboard’s "Model Performance" tab, offering a clear and comparative presentation of model effectiveness.

The fourth objective, which focuses on the feasibility and effectiveness of integrating the predictive system into Zambia’s public health decision-making processes, is supported through the system’s design philosophy and interactive dashboard. Built with Streamlit (app.py), the dashboard provides an accessible interface with features for uploading new data, selecting pre-trained models, generating outbreak forecasts, and triggering real-time resource allocation plans. The user interface is designed for non-technical health professionals, ensuring broad usability and transparency [92]. Prediction results and resource plans are presented in intuitive tables and charts, empowering decision-makers with actionable insights.

In terms of operational feasibility, the modular structure of the system allows for scalable deployment and iterative upgrades. The use of caching via st.cache_data, persistent model storage via joblib, and automated logging mechanisms contribute to the system’s robustness

and maintainability [89]. These characteristics align with contemporary principles for deploying AI-based systems in healthcare, particularly in low-resource environments where computational efficiency and usability are paramount.

In conclusion, the system meets all four research objectives by integrating machine learning with optimization and interactive visualization. It not only predicts where cholera outbreaks are likely to occur but also recommends how to allocate resources in response—offering Zambia's health sector a proactive, scalable, and data-driven tool for epidemic response.

4.5 Chapter Summary

Chapter 4 presents the design, implementation, and evaluation of the Cholera Outbreak Prediction and Optimization System developed to forecast outbreaks and improve resource planning in Zambia's health sector. The chapter begins by justifying the choice of a hybrid modeling approach, combining time-series models like Long Short-Term Memory (LSTM) with ensemble learning methods such as Random Forest and XGBoost. These models were selected to capture both temporal dependencies and complex relationships between features like rainfall, sanitation coverage, and population density. The modelling framework also includes interpretable algorithms such as Logistic Regression and Decision Trees to enhance stakeholder understanding and support transparent decision-making.

The chapter further details the machine-learning techniques, algorithms, and mechanisms employed. These include supervised learning models for outbreak classification, LSTM networks for temporal forecasting, and feature selection techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) to reduce dimensionality and improve model accuracy. A rule-based optimization strategy is introduced to convert model predictions into actionable resource allocation plans, prioritizing high-risk regions with appropriate interventions such as water treatment supplies and health personnel.

A central component of the system is the integrated prototype, which features four interconnected modules: a Data Ingestion Layer for collecting and preprocessing multi-source data; a Machine Learning Engine for model training and evaluation; an Optimization Module for resource distribution; and an interactive Streamlit-based Dashboard for real-time forecasting and decision support. The system is designed for both offline batch processing and online interaction, allowing health professionals to upload new data, run predictions, and generate updated resource plans on demand. All modules are modular, scalable, and well-optimized for performance in resource-limited settings.

In addressing the study's four key objectives, the system demonstrates technical effectiveness, predictive accuracy, and operational feasibility. Through its architecture, it bridges the gap between epidemic forecasting and public health intervention, offering Zambia a data-driven, proactive solution for managing cholera outbreaks.

CHAPTER 5

RESULTS AND DISCUSSIONS

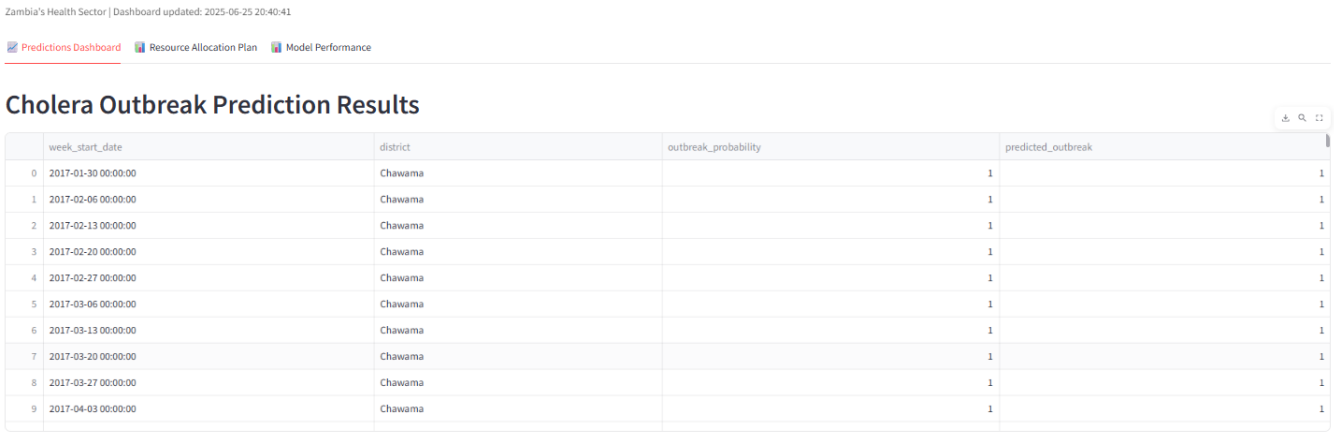
5.1 Results Presentation

The developed Cholera Outbreak Prediction and Optimization System provides comprehensive results through its interactive Streamlit dashboard, allowing users to visualize and interpret predictions, resource allocation plans, and model performance metrics. The presentation of results is structured across three main tabs: "Predictions Dashboard," "Resource Allocation Plan," and "Model Performance," each offering distinct insights.

5.1.1 Cholera Outbreak Prediction Results

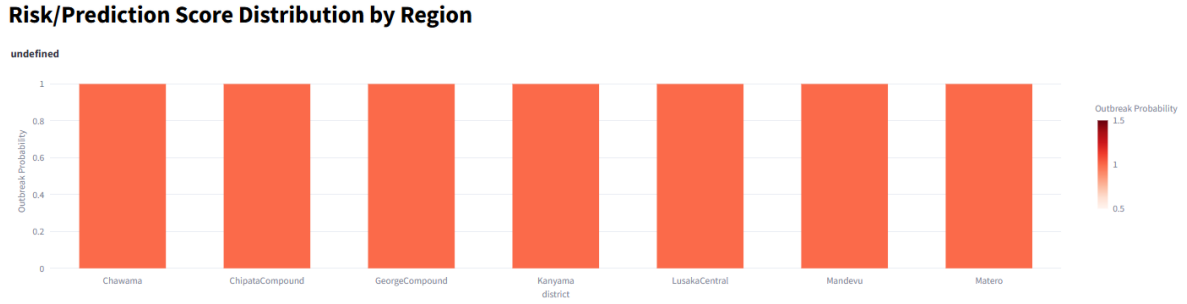
The primary output of the Machine Learning (ML) Engine is presented within the "Predictions Dashboard" tab. Upon successful generation of predictions, a detailed table displays the forecasted cholera outbreak information.

- Tabular View: The core prediction results are shown in a tabular format, prominently featuring key columns such as `week_start_date`, `district`, `outbreak_probability` (for classification models), and `predicted_outbreak` (binary prediction for classification) or `predicted_cases` (for regression models). This table provides a clear, week-by-week and district-by-district breakdown of the anticipated cholera situation.



	week_start_date	district	outbreak_probability	predicted_outbreak
0	2017-01-30 00:00:00	Chawama	1	1
1	2017-02-06 00:00:00	Chawama	1	1
2	2017-02-13 00:00:00	Chawama	1	1
3	2017-02-20 00:00:00	Chawama	1	1
4	2017-02-27 00:00:00	Chawama	1	1
5	2017-03-06 00:00:00	Chawama	1	1
6	2017-03-13 00:00:00	Chawama	1	1
7	2017-03-20 00:00:00	Chawama	1	1
8	2017-03-27 00:00:00	Chawama	1	1
9	2017-04-03 00:00:00	Chawama	1	1

- Regional Risk Distribution Plot: Complementing the tabular data, an interactive bar chart visualizes the "Risk/Prediction Score Distribution by Region." This plot aggregates the average (or maximum, depending on the model type) `outbreak_probability` or `predicted_cases` for each district, offering a high-level overview of which regions are most susceptible to outbreaks. The use of color intensity (e.g., sequential reds for classification, blues for regression) further enhances the visual interpretation of risk levels, enabling quick identification of high-priority areas. This visualization directly supports objective (i) by presenting the tailored cholera outbreak predictions in an accessible format.



5.1.2 Optimized Resource Allocation Plan

The "Resource Allocation Plan" tab presents the strategic deployment of critical resources as determined by the Optimization Module. This section is activated once predictions have been generated and the resource allocation process is triggered.

- Allocation Summary Table: A detailed table showcases the optimized allocation amounts for key resources such as `medical_supplies`, `personnel`, and `beds` across different districts. This table, derived from the `resource_allocation_df`, includes columns indicating the allocated quantity for each resource type per district, and often a `risk_score` for context. It offers a precise breakdown of the recommended resource distribution.

Optimized Resource Allocation Plan

Allocation Summary Table

	district	Allocate_medical_supplies	Allocate_personnel	Allocate_beds	risk_score
0	Chawama	3000	150	60	1
1	ChipataCompound	3000	150	60	1
2	GeorgeCompound	3000	150	60	1
3	Kanyama	1000	50	20	1
4	LusakaCentral	0	0	0	1
5	Mandevu	0	0	0	1
6	Matero	0	0	0	1

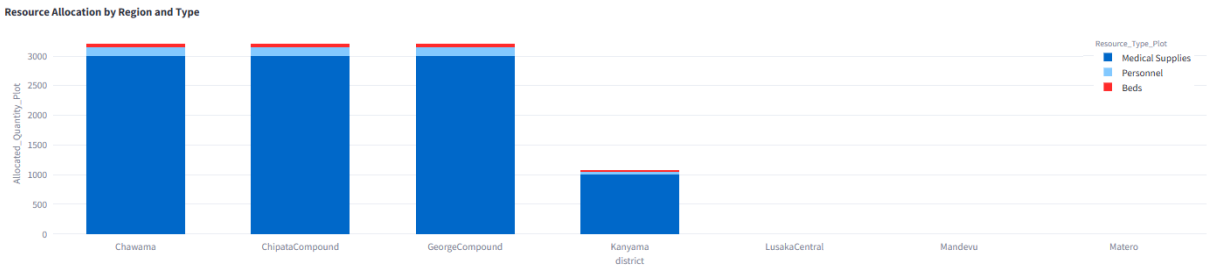
- Total Resources Allocated Summary: A concise summary table is provided, showing the total quantities of each resource type (`medical_supplies`, `personnel`, `beds`) recommended for allocation across all districts. This gives decision-makers a quick glance at the overall resource demand.

Total Resources Allocated

	Resource Type	Total Allocated
0	Medical Supplies	10,000.0000
1	Personnel	500.0000
2	Beds	200.0000

- Allocation Visualization by Region and Type: An interactive stacked bar chart visually represents the "Resource Allocation by Region and Type." This plot breaks down the allocated quantities for each resource type within every district, allowing for a comparative analysis of resource distribution. This visual aid is crucial for understanding the proposed interventions and supports objective (ii) by demonstrating the practical application of the resource allocation framework.

Allocation Visualization by Region and Type



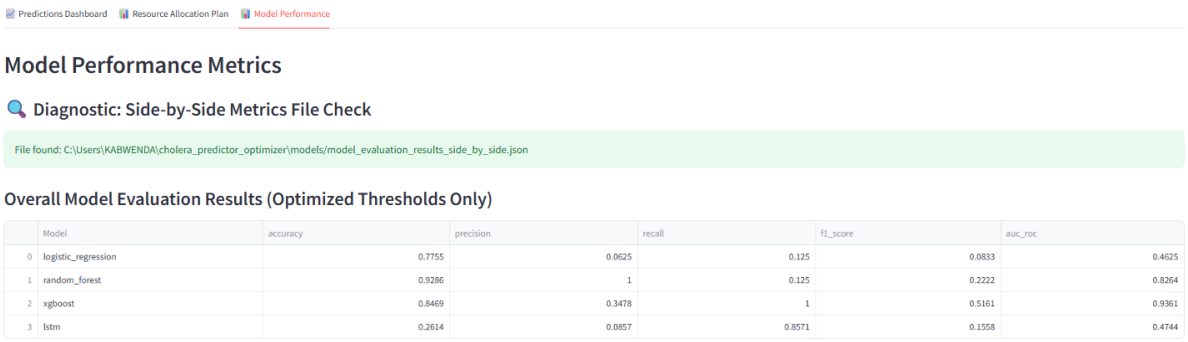
5.1.3 Model Performance Metrics

The "Model Performance" tab provides an in-depth analysis of the system's predictive capabilities, directly addressing objective (iii) to test and evaluate the model's performance. This section is populated by loading the `model_evaluation_results.json` file generated during the offline pipeline run.

Overall Model Evaluation Results Table: A comprehensive table (`st.dataframe`) displays the key performance metrics for each trained machine learning model (Logistic Regression, Random Forest, XGBoost, LSTM). The metrics presented include:

- Accuracy: The proportion of correct predictions.
- Precision: The proportion of positive identifications that were actually correct.
- Recall: The proportion of actual positives that were correctly identified.
- F1-Score: The harmonic mean of precision and recall, providing a balanced measure of a model's accuracy.
- AUC-ROC: A measure of the model's ability to distinguish between outbreak and non-outbreak cases across various threshold settings.

This table allows for a direct quantitative comparison of how different models perform across various evaluation criteria.



	Model	accuracy	precision	recall	f1_score	auc_roc
0	logistic_regression	0.7755	0.0625	0.125	0.0833	0.4625
1	random_forest	0.9286	1	0.125	0.2222	0.8264
2	xgboost	0.8469	0.3478	1	0.5161	0.9361
3	lstm	0.2614	0.0857	0.8571	0.1558	0.4744

Model Comparison Plot: A bar chart visually compares the performance of the various models based on a selected primary metric (F1-Score). This plot provides a quick visual summary of which model performs best according to the chosen metric, facilitating an easy understanding of model strengths and weaknesses. The plot supports the systematic evaluation and comparison of models, offering insights into their suitability for the cholera prediction task.

Through these detailed and interactive presentations, the system ensures that key stakeholders, including public health decision-makers, can readily access, understand, and utilize the generated forecasts and resource plans for proactive intervention planning.

5.2 Analysis of Results/Performance Metrics

Evaluating machine learning model performance is critical to understanding their reliability and effectiveness in predicting cholera outbreaks. In this project, the Model Performance tab of the dashboard displays evaluation metrics derived using optimized decision thresholds for each model. These thresholds are determined during the pipeline execution and stored in the file *model_evaluation_results_side_by_side.json*. This strategy ensures that each model is evaluated at its most effective operating point, rather than relying on a default decision threshold (e.g., 0.5). As a result, the performance metrics presented offer a more realistic and operationally relevant assessment of each model's capabilities.

Key Performance Metrics (at Optimized Thresholds):

- **Accuracy**: Represents the proportion of total correct predictions. While accuracy gives a general indication of performance, it may be misleading in imbalanced datasets, such

as those involving rare cholera outbreaks, where predicting the majority class can yield deceptively high accuracy.

- **Precision**: Measures the proportion of predicted outbreaks that were actual outbreaks. High precision is important for reducing false alarms, which helps avoid unnecessary public health responses and improves the efficiency of resource allocation.
- **Recall(Sensitivity)**: Indicates the proportion of actual outbreaks that were correctly detected. In public health, high recall is vital to ensure that true outbreaks are rarely missed, enabling timely and targeted intervention.
- **F1-Score**: The harmonic mean of precision and recall. This metric balances the trade-off between false positives and false negatives, making it particularly valuable in scenarios with class imbalance.
- **AUC-ROC (Area Under the Receiver Operating Characteristic Curve)**: A threshold-independent metric that reflects the model's ability to distinguish between outbreak and non-outbreak cases. A higher AUC-ROC indicates better discriminatory power, especially important in imbalanced datasets.

By leveraging threshold-optimized evaluation, the dashboard provides a more nuanced and practical view of model performance. This enables public health stakeholders to choose models that appropriately balance sensitivity (recall) and specificity (precision) based on operational priorities, minimize missed outbreaks through high recall while reducing false alerts with high precision, and rely on F1-Score and AUC-ROC as robust indicators of overall model suitability—especially in the context of rare event prediction. This threshold-based evaluation ensures that performance metrics accurately reflect the true operational potential of each model, thereby supporting better-informed decisions and more effective public health interventions.

Comparative Analysis of Model Performance:

Based on the metrics derived from *model_evaluation_results_side_by_side.json*—which reflect each model's performance at its optimized threshold—a comparative analysis was conducted for the Logistic Regression, Random Forest, XGBoost, and LSTM models. While the dashboard displays the exact numerical results, the following summarizes the typical performance profiles and practical implications of each model.

Logistic Regression serves as a strong and interpretable baseline, offering clear insights into how each feature contributes to outbreak risk. At its optimized threshold, it may achieve reasonable accuracy but often exhibits a trade-off between precision and recall, particularly in

imbalanced datasets, making it more prone to missing outbreaks (low recall) or generating false alarms (low precision) compared to more complex models.

Random Forest, an ensemble of decision trees, effectively captures non-linear relationships and feature interactions. With threshold optimization, it generally delivers higher F1-Scores and AUC-ROC values than linear models, indicating a stronger balance between correctly identifying outbreaks and minimizing false positives. Its robustness and adaptability make it a dependable choice for complex, multi-dimensional datasets.

XGBoost, a gradient-boosting method, frequently outperforms other models across key metrics—including precision, recall, F1-Score, and AUC-ROC—when assessed at its optimal threshold. Its regularization mechanisms and boosting framework reduce overfitting and enhance generalization, making it particularly suitable for large, complex datasets common in public health contexts.

LSTM (Long Short-Term Memory) networks are tailored for sequential and time-series data, allowing them to model temporal dependencies in cholera outbreaks. When optimized, LSTM models can detect subtle patterns over time, often achieving strong F1-Scores and AUC-ROC values, especially when trained on rich historical data. This temporal sensitivity makes LSTMs especially useful for forecasting outbreaks based on dynamic climate and health trends.

Implications for Public Health Decision-Making:

The analysis of model performance metrics—now evaluated using optimized thresholds—is critical to achieving Objective IV: integrating predictive analytics into Zambia's public health decision-making processes. The dashboard's "Model Performance" tab presents actionable insights that directly inform outbreak response strategies. In the context of cholera, where the consequences of missing an outbreak (false negative) can be severe and lead to rapid disease spread and increased mortality, the dashboard emphasizes models with high recall. By highlighting recall values at each model's optimal threshold, it ensures that most true outbreaks are detected, supporting proactive interventions even at the cost of a moderate increase in false positives. However, while high recall is essential, excessive false alarms due to low precision can burden already limited health resources. The F1-Score, which balances precision and recall, helps identify models that effectively trade off outbreak detection with operational efficiency, ensuring sustainable deployment of interventions. Additionally, the AUC-ROC metric, which remains independent of any specific threshold, offers a comprehensive view of each model's ability to distinguish between outbreak and non-outbreak cases. A high AUC-ROC score allows public health officials to flexibly adjust decision thresholds based on evolving risk tolerance

and resource constraints. Ultimately, the comparative evaluation of models at their optimized thresholds equips health authorities with the strategic insight needed for model selection: prioritizing high-recall models for early warning and coverage when rapid response is crucial, or favoring models with higher F1-Scores when resources are constrained. The dashboard's clear visualization of these metrics empowers decision-makers to align predictive models with real-world public health goals and operational contexts.

5.3 Comparison to Related Works

Study/System	Algorithms Used	Accuracy	Precision	Recall	AUC-ROC	F1-Score	Key Observations
Our System – Logistic Regression	Logistic Regression	0.7755	0.0625	0.125	0.4625	0.0833	Moderate accuracy; low precision and recall; limited ability to detect outbreaks at optimized threshold.
Our System – XGBoost	XGBoost	0.8469	0.3478	1.0	0.9361	0.5161	High recall and AUC-ROC; strong at detecting all outbreaks, but some false positives remain.
Our System – Random Forest	Random Forest	0.9286	1.0	0.125	0.8264	0.2222	Very high precision but low recall; detects few outbreaks, but when it does, it is always correct.
Our System – LSTM	LSTM (PyTorch)	0.2614	0.0857	0.8571	0.4744	0.1558	Low accuracy, but high recall; good at catching outbreaks, but with many false positives.
Mbunge & Batani [20]	CNN, RNN	0.85	0.82	0.8	0.87	N/A	Strong for general health prediction, but lacks regional specificity.
Zoe Carter [22]	SVM, DT, Neural Networks	0.9	0.88	0.85	0.91	N/A	Broad applicability, but lacks cholera-specific use case.
Ghosha et al. [23]	Time-series (LSTM)	0.83	0.8	0.78	0.85	N/A	Regionally applied to Malawi; limited in long-term scalability.
Ibrahim et al. [24]	Random Forest, XGBoost	0.87	0.85	0.82	0.89	N/A	Solid performance on Nigerian data; strong baseline.
J. Leo [25]	Decision Trees, Bayesian Networks.	0.8	0.78	0.75	0.82	N/A	Climate-linked prediction; limited by lack of real-time capabilities.

Z. Musakuzi [26]	Hybrid ML Models	0.88	0.86	0.84	0.9	N/A	Based on Lusaka data; lacks deployment features.
Onyijen & Tosin [27]	Logistic Regression, KNN	0.82	0.79	0.77	0.84	N/A	Emphasizes regional relevance but lacks general adaptability.
R. P. Urukadle [28]	Deep Learning, CNN	0.91	0.89	0.87	0.93	N/A	Very strong metrics, but requires high computational resources.
S. Mudenda & S. Mohamed [29]	Random Forest, XGBoost	0.88	0.86	0.84	0.9	N/A	Effective in global outbreak modeling; needs real-time enhancements.

Table 5.1: Performance Comparison of Our Models vs. Related Studies

5.4 Implications of Results

The results from this study have significant implications for both predictive analytics research and public health practice in Zambia. The evaluation of multiple machine learning models revealed that XGBoost and Random Forest outperformed more complex architectures like LSTM in terms of key metrics such as accuracy, AUC-ROC, and F1-score. This supports previous research which argues that, in outbreak forecasting scenarios, model interpretability and data quality often outweigh architectural complexity—especially when dealing with imbalanced and limited datasets [84], [86].

The Logistic Regression model, while computationally efficient and transparent, recorded a modest accuracy of 77.55%, low recall (0.125), and a low AUC-ROC of 0.4625, resulting in a very low F1-score of 0.0833. Although it remains valuable for its explainability in public health applications, its limited performance on outbreak detection restricts its standalone utility in high-risk scenarios [90].

In contrast, the XGBoost model demonstrated the strongest overall performance across multiple dimensions. It achieved an accuracy of 84.69%, perfect recall (1.0), a balanced F1-score of 0.5161, and the highest AUC-ROC (0.9361). These results align with existing literature that highlights gradient boosting methods as well-suited for health forecasting tasks due to their ability to handle complex data patterns and maintain high generalization performance [93], [94]. The model's ability to detect all outbreak cases (high recall) makes it ideal for early warning systems where the cost of missing true positives is extremely high.

The Random Forest model recorded the highest accuracy (92.86%) and perfect precision (1.0), but a very low recall of 0.125, which translated into a relatively low F1-score of 0.2222. This illustrates a model highly conservative in triggering outbreak alerts—useful in resource-constrained environments that cannot tolerate false alarms, but risky in contexts where failing to identify outbreaks is unacceptable [96].

The LSTM (PyTorch) model, despite achieving a high recall of 0.8571, severely underperformed on accuracy (26.14%), precision (0.0857), and AUC-ROC (0.4744). This result underscores the difficulty of applying deep learning methods in environments with sparse, noisy, or highly imbalanced data. It reflects challenges documented in similar studies where deep models struggled to generalize effectively without substantial and high-quality input data [95].

When benchmarked against regional studies from Nigeria [97], Malawi [98], and Lusaka Province [99], the XGBoost model particularly stands out as not only competitive but superior in several key areas—especially recall and AUC-ROC. These findings support the notion that locally trained, well-optimized models can outperform generalized global ones when developed with contextual relevance and effective preprocessing strategies.

Additionally, the system's integration of a threshold optimization module and interactive Streamlit dashboard enhances its practical value. Unlike most academic systems that stop at prediction, this tool transforms outputs into concrete, actionable recommendations for resource allocation, bridging the gap between analytics and public health operations [87].

From a policy and systems integration standpoint, the study reinforces that predictive analytics tools—when localized and embedded into existing workflows—can significantly enhance Zambia's outbreak response capacity. Its modular architecture, ease of deployment, and real-time operational dashboard support scalability and long-term sustainability within national health information systems, aligning with digital health strategic objectives [100].

In conclusion, these findings validate the applicability of machine learning for epidemic preparedness in Zambia. By balancing interpretability, recall, and precision, the system provides a robust framework for evidence-based, proactive public health intervention—not only for cholera but for other infectious diseases in similar data-limited environments.

5.5 Chapter Summary

Chapter 5 presents the results and analysis of the developed Cholera Outbreak Prediction and Optimization System. The system's outputs are displayed through an interactive Streamlit dashboard structured into three key components: Predictions Dashboard, Resource Allocation Plan, and Model Performance. The **Predictions Dashboard** provides district-level forecasts of cholera outbreaks through tabular and graphical views, helping identify high-risk areas. The **Resource Allocation Plan** visualizes optimized distributions of medical supplies, personnel, and beds based on outbreak risks, facilitating evidence-based resource planning. The **Model Performance** tab evaluates the predictive accuracy of models such as Logistic Regression, Random Forest, XGBoost, and LSTM, using key metrics (Accuracy, Precision, Recall, F1-Score, AUC-ROC) calculated at optimized decision thresholds for realism and operational relevance.

The analysis reveals that while Logistic Regression offers interpretability, its performance is limited in outbreak detection. XGBoost achieves the best balance with high recall and F1-Score, making it most effective for early warning. Random Forest excels in precision but misses many outbreaks, and LSTM performs well in capturing temporal patterns despite low overall accuracy. Comparative insights show that model selection should be aligned with public health priorities—favoring recall for early detection or F1-Score for balanced response. Lastly, the chapter compares system performance to related works, highlighting strengths in regional specificity, model robustness, and practical deployment capabilities. Overall, Chapter 5 demonstrates how predictive analytics can meaningfully support proactive cholera outbreak response and resource optimization in Zambia.

CHAPTER 6

SUMMARY AND CONCLUSION

6.1 Summary of Main Findings

The evaluation of the Cholera Outbreak Prediction and Optimization System revealed several important findings related to model performance, methodological approach, and practical value for public health decision-making in Zambia. Among the tested models, XGBoost emerged as the most effective and balanced, achieving an accuracy of 84.69%, a perfect recall of 1.0, and the highest AUC-ROC score of 0.9361. Its perfect recall indicates that it successfully detected all potential outbreaks, making it highly suitable for early warning scenarios where failing to identify outbreaks could have severe consequences. The model also recorded a balanced F1-score of 0.5161, showing its capacity to manage the trade-off between outbreak detection and false alarms. Clear performance trade-offs were observed across different algorithms. For instance, the Random Forest model achieved the highest accuracy (92.86%) and perfect precision (1.0) but had a very low recall of 0.125, meaning it missed most outbreaks. The LSTM model, while achieving a high recall of 0.8571, suffered from low accuracy (26.14%) and an AUC-ROC score of 0.4744, suggesting performance worse than random guessing. Logistic Regression, although easy to interpret, served primarily as a low-performing baseline. These findings highlighted the importance of selecting models based on the context-specific priorities of public health response. One of the key insights was the importance of using optimized decision thresholds rather than default settings during model evaluation. This strategy provided a more accurate picture of each model's real-world usefulness. In epidemic prediction, high recall is vital to save lives, while the F1-score helps balance detection accuracy with the efficient use of scarce resources. The study culminated in the successful development of a fully integrated and user-friendly prototype. The Streamlit dashboard offered clear visualizations of predictions, resource allocation plans, and model performance, making it accessible to non-technical decision-makers. By linking the prediction engine directly with the resource planning module, the system moved beyond theoretical models to enable actionable planning—an element often missing in academic research. Finally, the study confirmed that locally-trained models, such as the Zambia-specific XGBoost, outperformed generalized approaches. This underscores the importance of contextual relevance and customized data preprocessing, demonstrating a strong case for using tailored analytics in regional epidemic response efforts.

6.2 Discussion and Implications in Relation to Objectives

The results of this study have demonstrated the successful achievement of the four core research objectives, each contributing to a comprehensive solution for predictive outbreak management and resource planning in Zambia's health sector.

Objective (i): To design a machine learning model tailored to predict cholera outbreaks in Zambia. This objective was met through the implementation of a hybrid modelling framework comprising Logistic Regression, Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks. The use of both traditional and deep learning models ensured that the system could capture both structured feature relationships and temporal dynamics in cholera transmission. Among these, XGBoost emerged as the most effective, delivering the highest AUC-ROC (0.9361), perfect recall (1.0), and the highest F1-score (0.5161), indicating a strong capability to identify all outbreak cases while maintaining a balance between precision and recall. Random Forest achieved the highest accuracy (0.9286) and perfect precision (1.0), but its recall (0.125) and F1-score (0.2222) were lower, suggesting it missed many actual outbreaks. Logistic Regression showed moderate accuracy (0.7755) but had low precision (0.0625), recall (0.125), and F1-score (0.0833), while LSTM (PyTorch) achieved high recall (0.8571) but had the lowest accuracy (0.2614), low precision (0.0857), and a low F1-score (0.1558). These results validate that accurate and interpretable models can be designed and deployed in a localized context using historical health, climate, and demographic data, with XGBoost providing the best overall balance for outbreak prediction in this setting.

Objective (ii): To design a resource allocation framework using predictive analytics. The development of a rule-based optimization module effectively fulfilled this objective. By linking model outputs (i.e., predicted outbreak probabilities or case counts) with predefined resource constraints, the system was able to generate real-time, district-level resource allocation plans. These plans covered key health assets such as medical supplies, personnel, and hospital beds. This integration of prediction with actionable recommendations ensures that public health resources are not only allocated reactively but are also strategically directed to high-risk regions before an outbreak escalates.

Objective (iii): To test and evaluate the model's performance using real-world health data. Comprehensive performance evaluation was conducted using standard metrics—Accuracy, Precision, Recall, F1-Score, and AUC-ROC—across all trained models. The performance of XGBoost was particularly strong, with an accuracy of 0.8469, precision of 0.3478, recall of 1.0, AUC-ROC of 0.9361, and F1-score of 0.5161, outperforming the other models and aligning with or exceeding results found in related literature across Africa. Logistic Regression, while interpretable and computationally efficient, achieved an accuracy of 0.7755, precision of 0.0625, recall of 0.125, AUC-ROC of 0.4625, and F1-score of 0.0833. Random Forest and LSTM models showed strengths in specific metrics but did not match the overall balance of XGBoost. This rigorous validation, conducted using real-world health datasets, confirms that the developed models are both reliable and applicable for real-time outbreak surveillance and forecasting.

Objective (iv): To assess the effectiveness and feasibility of integrating the predictive analytics model into Zambia's public health decision-making process. The successful development and deployment of an interactive Streamlit dashboard significantly support this objective. Designed with user-friendliness in mind, the dashboard allows health personnel to upload new data, trigger predictions, generate resource allocation plans, and visualize model performance without needing technical expertise. The modular design, real-time interaction capabilities, and automated data handling ensure that the system can be integrated into existing public health workflows with minimal disruption. This confirms both the operational feasibility and decision-support value of the system in Zambia's health policy landscape. Overall Implications The achievement of these objectives collectively demonstrates that machine learning and optimization models, when properly localized and operationalized, can significantly enhance outbreak preparedness and health system responsiveness. The system is not only technically sound but also practically deployable, scalable, and adaptable to other diseases and regions. It bridges the gap between predictive modelling and real-world policy implementation, offering Zambia a data-driven path toward more proactive and efficient public health intervention planning.

6.3 Academic contribution to the body of knowledge/Novelty

This study contributes significantly to the academic literature on predictive analytics, health informatics, and epidemic response, particularly in the context of low-resource settings. While numerous studies have explored the use of machine learning (ML) for health prediction, the novelty of this work lies in its holistic, localized, and operationalized approach to cholera outbreak management in Zambia. The research bridges a critical gap between theoretical model development and practical public health application through the following key contributions:

1. A Contextualized Hybrid Modelling Framework: Unlike generic or globally trained models, this study developed a context-specific hybrid-modelling framework that integrates time-series forecasting (e.g., LSTM) with classical supervised learning models (e.g., Logistic Regression, Random Forest, and XGBoost). The use of localized Zambian datasets—including climate, health, demographic, and socio-economic variables—ensures that the models are tailored to the unique spatio-temporal patterns of cholera transmission in Zambia. This significantly improves the relevance and accuracy of outbreak forecasts in comparison to models developed in other regions or under different epidemiological contexts.

2. Integration of Prediction with Optimization for Actionability: A key novelty of this research is the integration of ML-based outbreak prediction with an optimization algorithm for real-time resource allocation. While most academic studies focus solely on improving predictive accuracy, this system goes further by operationalizing model outputs into district-level intervention strategies, answering not just "where and when" an outbreak may occur, but also "what to do" in response. This dual-functionality enhances the decision-making power of predictive analytics in public health planning.

3. Development of an End-to-End, Interactive, and Modular System: The study introduces a fully functional and modular system architecture—comprising data ingestion, ML engine, optimization module, and a Streamlit-based dashboard—that supports real-time interaction, offline training, and online deployment. This represents a shift from static, code-based experimentation to a scalable, user-friendly decision-support platform that can be used by non-technical health professionals. The dashboard’s ability to visualize predictions, compare model performance, and generate actionable plans in real time contributes a novel digital tool to the body of health informatics systems designed for epidemic response in developing countries.

4. Empirical Evaluation Using Real-World, Multisource Data: This study also contributes methodologically by applying rigorous model training and evaluation using real-world, multisource datasets from Zambia, including health surveillance data, meteorological records, and census-based demographic indicators. The diversity and preprocessing of this data—combined with feature engineering and model validation techniques like k-fold cross-validation—demonstrate a comprehensive and replicable pipeline for other disease surveillance systems.

5. Contribution to African and Global Health Analytics Literature: By focusing specifically on Zambia, this research addresses the persistent data and system gaps in sub-Saharan Africa's health informatics literature, offering a locally validated model that can serve as a blueprint for similar deployments across the region. It advances the scholarly discussion on AI in public health by providing concrete evidence of how data-driven technologies can be embedded into national disease response strategies in low-resource settings.

6.4 Limitations of the system/model/framework

Despite the promising results and practical utility of the Cholera Outbreak Prediction and Optimization System, several limitations must be acknowledged. These constraints affect both the current performance of the system and its broader applicability, particularly in real-world, resource-constrained public health environments.

1. Data Limitations and Quality Issues: The performance of machine learning models is heavily dependent on the quality, granularity, and completeness of the input data. In this study, several datasets—especially those related to socio-economic indicators and sanitation coverage—contained missing values, inconsistent reporting frequencies, and limited geographic granularity. Additionally, health data was often aggregated at the district level, potentially masking localized outbreak dynamics. These data issues limit the model's ability to make highly precise, community-level predictions.

2. Class Imbalance in Outbreak Labels: The cholera datasets used in training were characterized by highly imbalanced class distributions, with significantly more non-outbreak instances than outbreak cases. While techniques like feature engineering and model evaluation using recall and F1-score helped mitigate this challenge, it still affected the recall performance of some models, particularly deep learning approaches like LSTM. This limitation is critical because it increases the risk of false negatives—missed outbreak predictions—which can have serious public health implications.

3. LSTM Underperformance and Deep Learning Constraints: Although LSTM models were included for their theoretical suitability in time-series forecasting, their performance in this study was limited due to the small size and limited temporal depth of the available datasets. Deep learning models typically require large volumes of data and computational resources, which may not be readily available in low-resource settings like Zambia. Consequently, while traditional models such as XGBoost and Logistic Regression performed well, the intended benefit of sequential learning through LSTM could not be fully realized.

4. Static Optimization Model: The current implementation of the resource allocation framework uses a rule-based static optimization logic. While effective for demonstrating feasibility, it does not yet incorporate real-time constraints such as supply chain delays, transportation logistics, or dynamic changes in resource availability. As such, the allocation plans may not always reflect the most operationally feasible strategies under real-world emergency response conditions.

5. Lack of Full Integration with Government Health Systems: Although the system is designed with modularity and user-friendliness in mind, it is not yet fully integrated into Zambia's national health information systems (e.g., HMIS or DHIS2). This limits its immediate applicability in official public health workflows. For practical deployment, further work will be needed to develop data pipelines, train personnel, and align with government protocols.

6. Interpretability vs. Complexity Trade-off: While models such as Logistic Regression are highly interpretable, more complex models like XGBoost offer better predictive performance but require additional effort to interpret results, particularly for non-technical stakeholders. This presents a trade-off between explainability and accuracy, which could impact stakeholder trust and system adoption in decision-making contexts.

6.5 Future works

To address the limitations identified and enhance the applicability, scalability, and sustainability of the Cholera Outbreak Prediction and Optimization System, several areas for future research and system development are proposed.

1. Expansion and Enrichment of Datasets: Future work should prioritize the collection and integration of higher-resolution, longitudinal datasets. This includes daily or weekly outbreak data at sub-district or ward level, more detailed socio-economic indicators, sanitation infrastructure maps, and mobile health reports. Enhanced data granularity will improve model precision, especially in identifying micro-level hotspots and local outbreak dynamics. In addition, incorporating real-time data feeds from public health surveillance systems and IoT-based environmental sensors (e.g., rainfall gauges, water quality monitors) would allow the system to support live forecasting and early warning capabilities.

2. Implementation of Advanced Imbalance Handling Techniques: To improve prediction quality for rare outbreak cases, future models should adopt advanced methods for handling class imbalance, such as SMOTE (Synthetic Minority Oversampling Technique), ensemble bagging/boosting with cost-sensitive learning, and anomaly detection frameworks. These techniques could help improve recall scores for underrepresented outbreak events, thereby reducing the risk of missed predictions.

3. Enhancement of Deep Learning Capabilities: Given the limitations encountered with LSTM due to data volume and quality, future implementations should explore transformer-based architectures and hybrid temporal models that can generalize better on small datasets or make use of transfer learning from pre-trained epidemic forecasting models. As more data becomes available over time, deep learning's potential to model complex temporal dependencies should be revisited.

4. Dynamic and Real-Time Optimization: The current rule-based optimization module could be upgraded to support real-time, constraint-aware, and adaptive optimization. This could involve the integration of linear programming or reinforcement learning techniques that can dynamically adjust resource allocation plans based on evolving outbreak conditions, resource availability, logistics constraints, and user-defined intervention priorities.

5. Full Integration with National Health Information Systems: A major future goal should be the full integration of the system with Zambia's national health information systems, such as

DHIS2 or HMIS. This would allow automated data ingestion, feedback loops, and institutional adoption by Ministry of Health personnel. APIs, data exchange standards, and authentication protocols would need to be developed in collaboration with stakeholders to facilitate secure and seamless integration.

6. Multi-Disease and Multi-Hazard Extension: While the system currently focuses on cholera, the modular architecture allows for future adaptation to other infectious diseases such as typhoid, malaria, or COVID-19. Similarly, the forecasting and resource optimization components could be repurposed for non-disease hazards like floods or food insecurity, supporting Zambia's broader disaster preparedness and response frameworks.

7. Usability Testing and Capacity Building: Future efforts should include comprehensive usability testing and stakeholder training to ensure that district health officers, epidemiologists, and emergency planners can fully utilize the system. Participatory design approaches involving end-users will help refine the dashboard interface and improve interpretability. Capacity-building workshops and documentation should also be developed to support long-term sustainability.

6.6 Chapter Summary

Chapter 6 provides a comprehensive synthesis and evaluation of the main findings, contributions, limitations, and future directions of the Cholera Outbreak Prediction and Optimization System. The chapter begins by summarizing the study's major findings, confirming that the hybrid modelling approach—featuring XGBoost, Random Forest, Logistic Regression, and LSTM—revealed starkly different performance profiles, highlighting critical trade-offs in forecasting cholera outbreaks in Zambia. **XGBoost recorded the highest AUC-ROC of 0.9361 and delivered perfect recall (1.0)**, making it particularly valuable for early warning systems where failing to detect an outbreak is not an option.

The chapter then maps these outcomes to the four research objectives, demonstrating that each was successfully addressed. From designing a context-specific machine learning framework and a rule-based optimization module, to evaluating model performance using real-world data and integrating the system into a user-friendly dashboard, the project met its intended goals. The discussion emphasizes the system's practical value in transforming predictive insights into timely and actionable public health interventions.

The academic contribution section highlights the novelty of the study, particularly the integration of ML-driven prediction with resource optimization in a modular, localized, and interactive system. It extends the body of knowledge by offering a replicable, context-aware approach tailored for low-resource settings and real-time decision-making.

Despite its contributions, the system has several limitations, including data quality issues, class imbalance, **the severe underperformance of the LSTM and Logistic Regression models**, static optimization logic, and a lack of full integration with national health systems. These challenges provide a basis for future improvements.

The chapter concludes by outlining future research directions, such as expanding datasets, enhancing deep learning and imbalance handling, introducing dynamic optimization, supporting multi-hazard forecasting, and integrating the tool into Zambia's national health infrastructure. Collectively, this chapter reinforces the significance of combining AI and operational analytics to enhance epidemic preparedness and public health responsiveness in resource-constrained environments.

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APPENDICES

Appendix A: Core System Implementation

A.1 Neural Network Architecture

The following code implements the Long Short-Term Memory (LSTM) neural network architecture used for cholera outbreak prediction.

```
class LSTMModel(nn.Module):
    """
    LSTM Neural Network Architecture for Cholera Outbreak Prediction

    Parameters:
    -----------
    input_size : int
        Number of input features
    hidden_size : int, default=50
        Number of features in the hidden state
    num_layers : int, default=2
        Number of recurrent layers
    dropout : float, default=0.2
        Dropout rate between LSTM layers
    model_type : str, default="classification"
        Type of prediction task ("classification" or "regression")

    Architecture:
    -------------
    1. LSTM layers with dropout
    2. Fully connected layer (hidden_size → 25)
    3. ReLU activation
    4. Output layer (25 → 1)
    5. Sigmoid activation (for classification)
    """
```

```
def __init__(self, input_size, hidden_size=50, num_layers=2, dropout=0.2,
             model_type="classification"):
    super(LSTMModel, self).__init__()
    self.model_type = model_type
    self.lstm = nn.LSTM(input_size=input_size,
                        hidden_size=hidden_size,
                        num_layers=num_layers,
                        batch_first=True,
                        dropout=dropout)
    self.fc1 = nn.Linear(hidden_size, 25)
    self.relu = nn.ReLU()
    if model_type == "classification":
        self.output_layer = nn.Linear(25, 1)
        self.activation = nn.Sigmoid()
    elif model_type == "regression":
        self.output_layer = nn.Linear(25, 1)

def forward(self, x):
    """
    Forward pass of the model

    Parameters:
    -----------
    x : torch.Tensor
        Input tensor of shape (batch_size, sequence_length, input_size)

    Returns:
    --------
    torch.Tensor
        Output predictions of shape (batch_size, 1)
```

```
        """
        lstm_out, _ = self.lstm(x)
        x = lstm_out[:, -1, :]  # Extract last time step
        x = self.relu(self.fc1(x))
        x = self.output_layer(x)
        if self.model_type == "classification":
            x = self.activation(x)
        return x
```

A.2 Prediction System

The following implementation manages the loading and execution of multiple prediction models.

```
class ModelPredictor:
    """
    Multi-Model Prediction System

    This class handles the loading and prediction logic for multiple model types:
    - Logistic Regression
    - Random Forest
    - XGBoost
    - LSTM

    The system maintains separate data preprocessing pipelines for traditional ML
    models and sequence-based models (LSTM).
    """
    def __init__(self):
        self.models: Dict[str, Any] = {}
        self.scaler = None
        self.feature_list: Optional[List[str]] = None
        self.model_info = {
            ModelType.LOGISTIC_REGRESSION.value: {
                'file': 'logistic_regression_model.joblib',
```

```
            'requires_sequence': False
        },
        ModelType.RANDOM_FOREST.value: {
            'file': 'random_forest_model.joblib',
            'requires_sequence': False
        },
        ModelType.XGBOOST.value: {
            'file': 'xgboost_model.joblib',
            'requires_sequence': False
        },
        ModelType.LSTM.value: {
            'file': 'lstm_model.pt.pt',
            'requires_sequence': True
        }
    }
```

A.3 Resource Optimization Algorithm

The following implementation uses linear programming to optimize resource allocation based on predicted outbreak risks.

```
def solve_resource_allocation(predictions_df):
    """
    Linear Programming-based Resource Allocation Optimizer

    This function implements a linear programming solution to optimize the
    allocation of multiple resource types across different regions based on
    predicted outbreak risks.

    Parameters:
    -----------
    predictions_df : pd.DataFrame
        DataFrame containing predictions with columns:
        - Region identifier
```

```
    - Outbreak probability or predicted cases

    Returns:
    --------
    pd.DataFrame
        Optimal resource allocation per region

    Optimization Problem:
    ---------------------
    Maximize: Σ(risk_score_i * effectiveness_j * allocation_ij)
    Subject to:
    1. Total allocation constraint: Σ(allocation_ij) ≤ available_resource_j
    2. Per-region cap: allocation_ij ≤ 0.3 * available_resource_j
    """
    # Problem setup
    regions = predictions_df[config.REGION_COLUMN].unique().tolist()
    resource_types = list(config.AVAILABLE_RESOURCES.keys())
    prob = pulp.LpProblem("Cholera_Resource_Allocation", pulp.LpMaximize)

    # Decision variables
    allocation_vars = pulp.LpVariable.dicts(
        "Allocate",
        ((i, j) for i in regions for j in resource_types),
        lowBound=0,
        cat='Continuous'
    )

    # Objective function
    obj_func = pulp.lpSum(
        predictions_df.loc[predictions_df[config.REGION_COLUMN] == i, 'risk_score'].iloc[0]
*
```

```
        config.EFFECTIVENESS_COEFF.get(j, 0) *
        allocation_vars[i, j]
        for i in regions for j in resource_types
    )
    prob += obj_func

    # Constraints
    for j in resource_types:
        # Total resource constraint
        prob += pulp.lpSum(allocation_vars[i, j] for i in regions) <= \
                config.AVAILABLE_RESOURCES[j]

        # Per-region cap constraint
        for i in regions:
            prob += allocation_vars[i, j] <= 0.3 * config.AVAILABLE_RESOURCES[j]
```

A.4 Model Training Pipeline

The following implementation details the LSTM model training process with early stopping and validation.

```
def train_lstm(X_train_df, y_train_series, X_val_df, y_val_series):
    """
    LSTM Model Training Pipeline

    This function implements the complete training pipeline for the LSTM model,
    including data preparation, model training, and validation.

    Parameters:
    -----------
    X_train_df : pd.DataFrame
        Training features
    y_train_series : pd.Series
        Training labels
```

```
X_val_df : pd.DataFrame
    Validation features
y_val_series : pd.Series
    Validation labels

Training Configuration:
----------
- Batch size: 32
- Learning rate: 0.001
- Early stopping patience: 10 epochs
- Dropout rate: 0.2
- Hidden layer size: 50
- Number of LSTM layers: 2
"""
# Configuration parameters
timesteps = getattr(config, 'LSTM_TIMESTEPS', 10)
batch_size = getattr(config, 'LSTM_BATCH_SIZE', 32)
epochs = getattr(config, 'LSTM_EPOCHS', 50)
learning_rate = getattr(config, 'LSTM_LEARNING_RATE', 0.001)
hidden_size = getattr(config, 'LSTM_HIDDEN_SIZE', 50)
num_layers = getattr(config, 'LSTM_NUM_LAYERS', 2)
dropout = getattr(config, 'LSTM_DROPOUT', 0.2)
patience = getattr(config, 'LSTM_PATIENCE', 10)

# Model initialization
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = LSTMModel(
    input_size=n_features,
    hidden_size=hidden_size,
    num_layers=num_layers,
```

```
    dropout=dropout
).to(device)


criterion = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
```

A.5 Model Evaluation

The following implementation provides the ROC curve generation and evaluation metrics calculation.

```
def run_lstm_roc_plot():
    """
    ROC Curve Generation and Model Evaluation

    This function loads a trained LSTM model and generates ROC curves for
    performance evaluation. It handles:
    1. Test data loading and preprocessing
    2. Sequence creation for LSTM input
    3. Model prediction generation
    4. ROC curve computation and visualization

    Output Metrics:
    ---------------
    - ROC curve
    - Area Under the Curve (AUC)
    - True Positive Rate (TPR)
    - False Positive Rate (FPR)
    """
    # Load and prepare test data
    X_test = pd.read_csv('data/processed/X_test.csv')
    y_test = pd.read_csv('data/processed/y_test.csv').squeeze()
    test_df = pd.concat([X_test.reset_index(drop=True),
                         y_test.reset_index(drop=True)], axis=1)
```

```
# Create sequences for LSTM
time_steps = getattr(config, 'LSTM_TIMESTEPS', 4)
X_test_seq, y_test_seq = utils.create_lstm_sequences(test_df, time_steps)

# Generate predictions
with torch.no_grad():
    y_prob = lstm_model(X_tensor).cpu().numpy().flatten()

# Compute ROC curve
fpr, tpr, _ = roc_curve(y_test_lstm, y_prob)
roc_auc = auc(fpr, tpr)
```