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AFRICA CENTER OF EXCELLENCE IN INTERNET OF THINGS (ICE- IoT)

Research Thesis Title:

Enhanced urban disaster response using IoT -GIS with real time data analytics and ML

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Degree in Internet of Things: Embedded Computing Systems*

Submitted by:

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July, 2025

DECLARATION

I, the undersigned, declare that this Project proposal is my original work, and has not been presented for a degree in University of Rwanda or any other universities. All sources of materials that will be used for the thesis work will have been fully acknowledged in the correct academic format.

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BONAFIDE CERTIFICATE

This is to certify that this submitted Research Thesis work report is a record of the original work done by SIKINDI Jean Baptiste (**Ref. No:** 222022092), Masters in IoT- Wireless Intelligent Sensors Networking Student at the University of Rwanda / College of Science and Technology / African Center of Excellence in the Internet of Things, the Academic year 2022/2024.

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ABSTRACT

Urban disasters, including floods, earthquakes, and infrastructure failures, position significant challenges to modern cities, often resulting in severe consequences such as loss of life, economic disruption, and long recovery periods. Many rapidly urbanizing cities, faces increasing disaster risks due to infrastructure weakness and a lack of advanced integrated technologies for disaster management. Current approaches are frequently reactive, relying on limited data and manual coordination, which delays responses and leads to inefficient resource allocation. This project aims to bridge these gaps by developing an advanced emergency management system that integrates Internet of Things (IoT) sensors, Geographic Information System technology, real-time data analytics, and machine learning (ML). IoT sensors deployed across urban areas to continuously monitor environmental and infrastructural conditions, generating real-time data critical for rapid disaster detection and response. GIS technology enable spatial mapping and analysis of disaster impacts, providing detailed insights into affected areas and supporting informed decision-making. Real-time data analytics process these streams to deliver actionable insights to emergency responders, while ML algorithms leverage historical data to predict potential disaster scenarios, optimize resource allocation, and enhance decision-making accuracy. The system improve disaster response times, reduce risks to human life, and bolster urban resilience. Key outcomes include real-time monitoring, predictive disaster models, and a robust IoT-GIS-based emergency management platform. These results distributed through academic publications, workshops, and conferences, promoting the adoption of advanced disaster management solutions. By addressing critical gaps in disaster preparedness, the project enhance public safety, minimize disaster impacts, and provide a scalable model for other cities worldwide. Ultimately, it seeks to establish a new standard for urban disaster preparedness and response, ensuring a more resilient future for cities.

Key terms: IoT Sensors, Geographic Information System technology, Real-Time Data Analytics, Machine Learning, Emergency Response

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LIST OF ACRONYMS

IoT – Internet of Things

GIS – Geographic Information System

ACEIoT – African Center of Excellence in Internet of Things

UR – University of Rwanda

GPS – Global Positioning System

SMS – Short Message Service

URL – Uniform Resource Locator

API – Application Programming Interface

HTML – HyperText Markup Language

HTTP – HyperText Transfer Protocol

LED – Light Emitting Diode

LCD – Liquid Crystal Display

CPU – Central Processing Unit

RAM – Random Access Memory

USB – Universal Serial Bus

GUI – Graphical User Interface

IP – Internet Protocol

MQTT – Message Queuing Telemetry Transport

AI – Artificial Intelligence

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Disasters have a major negative impact around the world. The Global Assessment Report on Disaster Risk Reduction 2022 shows that each year, between 2001 and 2020, there were between 350 and 500 medium and large disasters. In 2021, natural disasters caused 10,492 deaths and affected over 104 million people globally [1].

Disasters cause significant damage, improving disaster management in cities is very important. One effective way to do this is by combining Building Information Modeling (BIM) with Geographic Information Systems (GIS) [2]. According to Zhu and Wu, BIM-GIS integration means using both technologies together to solve real-world problems. BIM provides detailed information about buildings and their internal structures, while GIS adds geospatial data and strong analysis tools. By combining the strengths of both, we can better handle urban challenges, managing disasters [3].

Urban disaster management is one of the many businesses that has benefited greatly from the quick growth of technology, especially in the field of the Internet of Things (IoT). An unprecedented level of capability in disaster response and management is made possible by the Internet of Things (IoT), which is a network of networked devices that can gather, process, and transmit data in real-time. Traditional disaster response procedures frequently fall short in terms of speed, accuracy, and efficacy in urban regions, particularly in expanding cities like Rwanda's Kigali, Butare, and Musanze, where population density and complex infrastructure present specific obstacles. These rapidly urbanizing and infrastructural developing Rwandan cities face many obstacles, including inadequate situational awareness during disasters, ineffective resource allocation, and delayed emergency services. Given Rwanda's geographic vulnerability to natural disasters floods and landslides, these problems are especially severe, and the urgent need for effective emergency management systems is growing [4]. The capacity of the Internet of Things to easily connect and integrate physical devices and sensors to collect and share data in real time is what makes it so essential. The utilization of real-time data is crucial in enabling well-informed decision-making and optimizing diverse urban catastrophe response activities, such as crisis communication and emergency resource management. Urban planners and emergency responders in places Kigali, Butare, and Musanze may gather data in real time on human activity, infrastructure status, and environmental conditions by integrating IoT sensors and devices throughout urban landscapes. Geographic Information Systems (GIS) and the Internet of Things (IoT)

combine to enable the viewing and analysis of this data in spatial contexts, offering in-depth understanding of the effects of disasters and enabling accurate, timely actions [5].

Furthermore, by using machine learning algorithms to evaluate data trends, forecast disaster outcomes, and improve reaction plans, these IoT-GIS systems are further improved. By continuously learning from historical data and real-time events, these technologies enhance overall catastrophe management efficiency and adjust to changing urban needs. In order to minimize casualties, reduce response times, and lessen the damage caused by disasters in cities Kigali, Butare, and Musanze, a strong framework for real-time monitoring, predictive analytics, and automated decision-making is created by combining IoT, GIS, and machine learning [6].

This study examines how IoT technology has developed and how it has revolutionized urban disaster response systems, with special attention to Rwandan cities. We explore how the complexity of urban disaster scenarios might be addressed by an integrated IoT-GIS emergency management system, emphasizing how this system can improve real-time situational awareness, resource allocation, and decision-making. In order to maximize urban catastrophe response and increase resilience and response efficacy in urban environments such as those in Rwanda, we suggest a holistic system that makes use of IoT sensors, GIS mapping, real-time data analytics, and machine learning. With regard to cities that are experiencing rapid growth and increased susceptibility to both natural and man-made dangers, this strategy seeks to establish new benchmarks for disaster management [7].

1.2 Motivation of the study

Urban disasters have caused significant loss of life and economic disruption, highlighting the need for advanced disaster management systems. This study aims to develop an integrated IoT-GIS emergency management system, utilizing real-time data analytics and machine learning to enhance disaster response. The system's goals include improving situational awareness, optimizing response strategies, and minimizing disaster impacts. The benefits include enhanced public safety, reduced economic losses, and a scalable model for other cities.

1.3 Problem statement

In Rwandan cities, ineffective resource allocation, outdated processes, and poor reaction times all contribute to problems with urban disaster management. Lack of real-time data integration makes these problems worse and causes inefficient and delayed emergency responses. Urban areas need an

integrated IoT-GIS emergency management system to improve situational awareness, optimize disaster response, and build overall flexibility. This system uses real-time data analytics and machine learning.

1.4 Objective

1.4.1 Main objective

The main objective of this work was to enhance urban disaster response using IoT -GIS with real time data analytics and ML.

1.4.2 Specific objectives

1. To design IoT devices for disaster detection.
2. To create a real-time dashboard for report.
3. To develop machine learning models for disaster prediction and response optimization.
4. To send alert notification to the citizens.

1.5 Hypotheses

The hypotheses of this study are centered on the potential impact of integrating IoT, GIS, and machine learning technologies in urban disaster management. It is hypothesized that the combination of IoT sensors with GIS-based real-time data analytics significantly enhance the accuracy and timeliness of disaster detection and response, reducing disaster response times compared to traditional methods. Additionally, the incorporation of machine learning algorithms improve disaster prediction and mitigation by identifying patterns from historical and real-time data, thereby optimizing decision making during crises. The study also hypothesizes that the deployment of this system in Kigali result in reduced financial losses and fatalities, improving overall disaster preparedness, response coordination, and resource allocation. Furthermore, it is believed that this IoT-GIS system serve as an effective and scalable model for other cities, advancing global disaster management practices.

1.6 Study Scope

This study focuses on the development and implementation of an integrated IoT-GIS emergency management system tailored for urban disaster response in Kigali, Rwanda. The scope of the study includes the deployment of IoT sensors throughout urban regions to collect real-time data on environmental and infrastructural conditions, as well as the use of GIS technology for spatial data analysis. The system aims to improve situational awareness and response strategies during disasters floods, earthquakes, and infrastructure failures. Additionally, the study explores the application of

machine learning algorithms to enhance predictive capabilities and decision-making processes. The study primarily assess the effectiveness of this integrated system within Kigali's urban environment, while also evaluating its potential scalability to other cities. The study not include the development of communication systems Wi-Fi-based notifications but focus on real-time data processing, analytics, and decision-making support.

1.7 Significance of the Study

The significance of this study lies in its ability to address the challenges of urban disaster management by integrating IoT, GIS, and machine learning technologies into a cohesive system. By providing realtime monitoring, predictive analytics, the system enhances the accuracy, speed, and effectiveness of disaster response. It benefits society by improving public safety, reducing loss of life, minimizing economic losses, and strengthening urban resilience. For the field of disaster management, the study introduces an innovative and scalable framework that can be adopted globally, setting new standards for proactive disaster mitigation. Additionally, it empowers policymakers with data-driven visions for better urban planning and resource allocation. The study also fills a critical research gap, contributing valuable knowledge to the advancement of technology-enabled disaster preparedness and resilient urban infrastructure.

1.8 Organization of the Study

This study is organized into six chapters, each addressing a critical aspect of the research. Chapter 1 introduces the study by outlining the background, motivation, problem statement, objectives, hypotheses, scope, and significance, setting the foundation for understanding the research context. Chapter 2 reviews existing literature on IoT-GIS technologies, machine learning, and disaster management systems, identifying research gaps and explaining how this study addresses them. Chapter 3 details the research methodology, including design, data collection techniques, and implementation strategies to achieve the study's objectives. Chapter 4 focuses on system analysis and design, presenting architectural frameworks, data flow models, and simulations to demonstrate the proposed solution's feasibility. Chapter 5 presents the findings using graphs, tables, and statistical analyses to evaluate the system's performance in improving urban disaster response. Finally, Chapter 6 summarizes key findings, offers practical recommendations, and suggests directions for future research, concluding with a detailed list of references to ensure proper citation and support for the study.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Urban areas worldwide are increasingly vulnerable to a complex array of natural and man-made disasters, from climate change-induced extreme weather events like floods and droughts to geological hazards, pandemics, and technological failures. The rapid urbanization, particularly in developing nations such as Rwanda, exacerbates this vulnerability by concentrating populations and critical infrastructure, thereby amplifying the potential for catastrophic impacts. Traditional disaster response mechanisms, often reliant on manual processes, disparate information systems, and retrospective analysis, frequently struggle to cope with the speed, scale, and complexity of modern urban emergencies. This necessitates a paradigm shift towards more proactive, intelligent, and integrated approaches to emergency management. [7].

In recent years, the convergence of transformative technologies – notably the Internet of Things (IoT), Geographic Information Systems (GIS), real-time data analytics, and Machine Learning (ML) – has opened unprecedented opportunities for revolutionizing urban disaster response. These technologies promise to enhance situational awareness, enable predictive capabilities, facilitate dynamic resource allocation, and ultimately optimize the entire disaster management cycle from preparedness and early warning to response and recovery.

This literature review aims to provide a comprehensive overview of existing research and projects at the intersection of these critical technological domains and disaster management. It will explore the evolution of emergency management systems, the role of IoT in real-time data collection, the indispensability of GIS for spatial intelligence, and the burgeoning application of real-time data analytics and machine learning for predictive modeling and operational optimization. By critically examining the state-of-the-art, identifying established methodologies, and highlighting current gaps, this review will establish the theoretical and empirical foundation for the proposed Integrated IoT-GIS Emergency Management System, demonstrating the pressing need for a holistic, intelligent, and optimized approach to urban disaster response.

2.2 Future Trends in Disaster Response Systems

The incorporation of IoT technology has greatly improved the situational awareness and operational efficiency of urban disaster response systems. IoT sensors and real-time data exchange seamlessly connect with Geographic Information Systems (GIS) to provide a spatially-aware understanding of

disaster consequences by expediting data collecting and improving real-time decision-making. Nonetheless, there are still important issues to be addressed, such as compatibility with the current metropolitan infrastructure and strong data security measures to safeguard critical information. Important topics for improvement include enhancing real-time analytics capabilities to forecast trends of disasters and enhancing the scalability of IoT networks in various urban location [8].

Because IoT and GIS technologies allow for real-time resource tracking and environmental monitoring, disaster management has become more accurate and transparent. Notwithstanding these advantages, there are a number of important drawbacks, such as the high initial setup costs, compatibility problems with older municipal infrastructure, and the requirement for standardization in order to guarantee widespread acceptance and interoperability in various urban environments. Subsequent investigations might concentrate on optimizing the integration of IoT and GIS technologies to lower implementation expenses and enhance system compatibility [9].

Urban catastrophe management has undergone a revolution thanks to machine learning, which has shortened reaction times, predicted the effects of disasters, and optimized resource allocation. The requirement for sizable datasets for precise forecasts, maintaining algorithm transparency for legal compliance, and fusing machine learning with current emergency management systems to improve operational effectiveness are just a few of the major obstacles that still need to be overcome. Future research might concentrate on creating explainable AI models to boost public confidence in local government representatives and citizens, as well as using federated learning to safeguard privacy and facilitate cooperative data analysis across urban catastrophe management networks [10].

Real-time data analytics facilitate proactive monitoring of urban disaster situations by offering valuable insights into disaster trends and response efficiency. Concerns about data privacy, the difficulty of putting real-time analytics infrastructure into place, and guaranteeing data accuracy and dependability in a variety of urban settings are some of the main obstacles. Potential avenues for future development could include utilizing cutting-edge anomaly detection algorithms to stop fraud and improve emergency response procedures, utilizing edge computing technologies to process data closer to the point of origin, and enhancing decisions made in real time [11].

By using decentralized ledgers and cryptographic protocols, blockchain technology improves the security and integrity of data used in disaster management. Difficulties include the need to integrate blockchain technology with current urban IT systems, legislative difficulties around the use of blockchain in disaster management, and constraints on scalability. Possible directions for future study could include investigating legislative frameworks that support the use of blockchain technology in

urban disaster response, as well as finding solutions to scalability problems via improvements in consensus algorithms. In order to address the unique requirements of urban catastrophe management systems, research could also look into hybrid blockchain solutions that strike a compromise between privacy and transparency requirements [12].

2.3 IoT-Based Early Warning Systems for Specific Hazards

2.3.1 Introduction

Effective disaster response is predicated on timely and accurate early warning. Recent advancements in the Internet of Things (IoT) have enabled the development of localized monitoring systems for specific natural hazards, offering crucial initial alerts

2.3.2 Related work

The study by Harerimana (2022), "An IoT Based Landslide Monitoring Using Fuzzy Logic Driven Early Warning System," from the University of Rwanda, offers valuable insights into IoT-driven early warning systems. Methodologically, the project developed a prototype integrating soil moisture, accelerometer, and vibration sensors with an Arduino microcontroller to capture real-time landslide precursors. Its primary innovation lies in employing Fuzzy Logic directly on the microcontroller (edge computing), enabling intelligent, localized risk assessment and timely SMS alerts via GPRS/GSM, making it robust for areas with limited internet. However, while effective for localized landslide prediction and early warning, the project presents several key gaps for broader urban disaster response: it is hazard-specific (only landslides), lacks deep spatial integration with a comprehensive GIS for wider situational awareness and resource mapping, and its use of machine learning (Fuzzy Logic) is confined to prediction rather than optimizing the complex, multi-faceted response operations across an entire urban environment.

The doctoral thesis by Kuradusenge (2022), Predictive Modelling and Alert System for Rainfall Induced Landslides, also from the University of Rwanda's ACEIoT, significantly contributes to landslide early warning. Methodologically, this research leverages machine learning models, specifically Random Forest (RF) and Logistic Regression (LR), to predict rainfall-induced landslides. A key innovation is the emphasis on incorporating antecedent cumulative rainfall data alongside other internal (e.g., slope angle, soil type) and external factors, significantly improving prediction accuracy (with AUC values reaching 0.997). The study identified strong correlations between antecedent precipitation and landslide occurrences and designed an early warning system prototype based on determined rainfall and soil moisture thresholds, using wireless sensors for data collection. However, despite its advanced predictive capabilities,

Kuradusenge's work, like similar efforts, primarily focuses on site-specific landslide prediction and alert issuance. It lacks broader integration with a GIS platform for real-time spatial visualization and comprehensive urban-scale disaster management. Furthermore, while excellent for predicting a singular hazard, it does not extend its machine learning capabilities to optimize dynamic response operations across multiple concurrent urban incidents, which is crucial for a holistic emergency management system.

The study by Myeong et al. (2019), "An IoT-Based Smart City Fire Detection and Prediction System using Machine Learning," demonstrates an integrated approach to urban safety in South Korea. Methodologically, it leverages a distributed network of IoT sensors (temperature, smoke, gas) for real-time data collection across urban areas. Innovation lies in applying machine learning models (e.g., Support Vector Machine, Artificial Neural Networks) to analyze this data for accurate fire prediction and early warning. The system integrates sensor data with a web-based GIS for visualizing fire risk zones. However, a significant gap from your perspective is its hazard-specificity to fires, limiting its multi-hazard applicability. While it uses ML for prediction, it doesn't extensively detail how ML optimizes dynamic response logistics (e.g., adaptive routing for fire trucks based on real-time traffic and incident spread) across a broader urban disaster scenario beyond initial detection.

Research by Li et al. (2021), "A Real-Time Urban Flood Monitoring and Early Warning System Based on IoT and GIS," from China, highlights an effective system for hydrological hazards. Methodologically, the system integrates IoT-based water level and rainfall sensors with a GIS platform to create a real-time, visual dashboard of flood conditions. Its innovation is in providing immediate spatial awareness of flood inundation and potential risk areas through the GIS, enabling faster decision-making for authorities. Real-time data analytics continuously updates flood models for improved warning accuracy. Nevertheless, a primary gap is the exclusive focus on flood monitoring, which, while critical, doesn't address the integrated management of diverse urban disasters. Furthermore, while it offers real-time visualization, the paper doesn't explicitly delve into how advanced machine learning is used to optimize the complex response actions like resource allocation or evacuation path recommendations based on dynamic, multi-factor data streams.

The work by Chen et al. (2020), "AI-Powered Damage Assessment and Resource Allocation for Post-Disaster Response in Smart Cities," conducted in a simulated smart city environment, focuses on the crucial post-disaster phase. Methodologically, this study utilizes deep learning (e.g., CNNs) for automated damage assessment from drone imagery, feeding this intelligence into a multi-agent reinforcement learning (MARL) framework to optimize emergency resource allocation (e.g., assigning rescue teams, medical

supplies). The innovation lies in its use of advanced AI for both rapid situational understanding and complex, dynamic resource optimization in a damaged urban landscape. However, a key gap is its primary focus on the post-disaster response phase and simulated environment, rather than incorporating real-time, pre-disaster or in-disaster early warning and monitoring from diverse IoT sensors for proactive intervention. It also doesn't detail the overarching GIS platform that would integrate continuous monitoring with optimized response in real-time across the entire disaster lifecycle.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the research methodology employed in the design and implementation of the enhanced urban disaster response system integrating IoT, GIS, real-time data analytics, and machine learning. The methodology provides a structured framework, ensuring clarity and precision in executing the project objectives [13]. A well-defined methodology is vital for developing a robust and scalable solution for effective disaster preparedness and management.

The research design serves as the comprehensive framework and roadmap for this study, guiding the systematic integration of IoT devices, GIS systems, machine learning models, and real-time data analytics to develop an intelligent urban disaster response solution [14]. The design is structured to address the core challenges of disaster management, including early detection, rapid response, efficient resource allocation, and predictive insights for mitigating risks.

3.2 Research Design

The design emphasizes the iterative development and testing of system components to ensure reliability, scalability, and adaptability to various disaster scenarios. It involves identifying and deploying suitable hardware and software tools to collect and process environmental data, flood levels and earthquakes activity. The IoT infrastructure forms the backbone of the system, enabling continuous data acquisition from strategically placed sensors in disaster-prone urban areas. Machine learning models are incorporated to analyze collected data, detect patterns, and predict potential disaster events, enhancing preparedness and proactive measures. Real-time data analytics ensures that emergency response teams receive actionable insights promptly, enabling faster and more informed decisionmaking during critical situations [15]. The design also includes mechanisms for stakeholder feedback and performance evaluation, ensuring that the system aligns with real-world disaster management needs.

3.3 Data Collection and Visualization

Data collection for this study focuses on Kigali City, integrating IoT sensors, GIS mapping, and realtime analytics to enhance disaster response. The system uses two primary data sources: water level sensors for detecting rising water levels in flood-prone areas and vibration and earthquake activity sensors for monitoring seismic events. These sensors transmit real-time data to a central cloud-based

database via wireless communication protocols. This approach ensures accurate, reliable information for disaster preparedness. The collected data is securely stored and processed for analysis, supporting early warning systems and enabling authorities to implement proactive measures for risk mitigation.

To enhance decision-making, the system employs GIS-based mapping for visualizing geospatial data, allowing emergency response teams to identify high-risk zones and optimize resource allocation. Interactive dashboards and GIS tools display real-time sensor readings, historical trends, and predictive insights. The Random Forest Classifier is used to analyze disaster patterns and classify risk levels, providing early warnings and actionable recommendations. This integration of IoT-driven monitoring, GIS-based visualization, and machine learning enables an intelligent disaster management framework, ensuring timely interventions and an efficient response strategy in Kigali City.

3.3.1 Flood Data

Kigali, the capital of Rwanda, is situated at the country's geographical center. In 2023, the city has rapidly developed into a modern urban hub, serving as Rwanda's primary commercial center and a key entry point [16]. However, Kigali's hilly terrain, characterized by steep slopes, interconnected ridges, and valleys, makes it highly susceptible to flooding, especially during heavy rainfall [17]. Rapid urbanization has contributed to increased surface runoff, reduced natural water absorption, and the encroachment of wetlands, exacerbating the flood problem in several parts of the city.

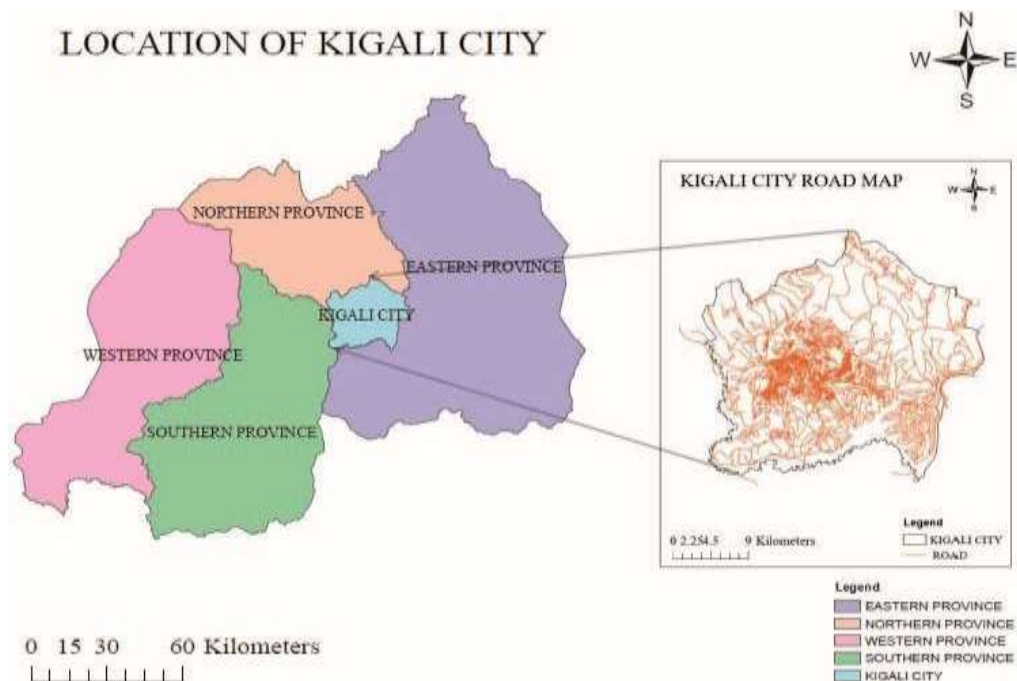


Figure 1: Location of kigali

The Nyabugogo River, the most significant waterway in Kigali, plays a crucial role in the city's drainage system, eventually merging with the Nyabarongo River. Covering most of the city's territory, the Nyabugogo River basin is particularly prone to seasonal flooding, affecting key infrastructure, businesses, and residential areas. The Nyabarongo River, which forms the southern and western borders of Kigali, lies just outside the built-up urban area but influences the city's flood dynamics. These rivers are surrounded by wetlands that serve as natural water reserves and flood barriers. However, ongoing agricultural expansion, deforestation, and urban development threaten these wetlands, reducing their capacity to absorb excess water and increasing the frequency and severity of floods in Kigali [18].

Flooding in even a small part of Kigali's road network can create big problems across the city. It affects how traffic moves, causing fewer vehicles on the road, lower speed limits, and longer travel times. Many people struggle to reach their destinations on time due to water-covered roads. Nyabugogo wetland, located in Kigali, is one of the places most affected by floods. Heavy rains often cause water to overflow, making roads difficult to use. This leads to traffic jams, vehicle breakdowns, and accidents. Motorists, cyclists, and pedestrians all face challenges when moving through flooded areas. Businesses in flood-prone areas also suffer because transportation slows down [19]. Floods not only damage roads but also affect daily life, making movement in the city stressful. Better drainage systems and flood control measures are needed to reduce the impact of flooding in Kigali.



Figure 2: Effect of flood in Kigali

3.3.1 Earthquake Data

The map below showing the latest earthquakes near Kigali, Rwanda. The red circles indicate earthquake occurrences, with their size representing the intensity or affected area. The blue marker is likely

pinpointing Kigali's location. The earthquake activity is concentrated along the western part of Rwanda, extending into Burundi and the eastern Democratic Republic of the Congo. This region is part of the East African Rift System, known for frequent seismic activity due to tectonic movements. The clustering of red circles suggests a series of recent earthquakes or aftershocks along this fault line, which could pose risks to infrastructure and communities in Kigali and nearby areas [20].

Map of Latest Earthquakes near Kigali

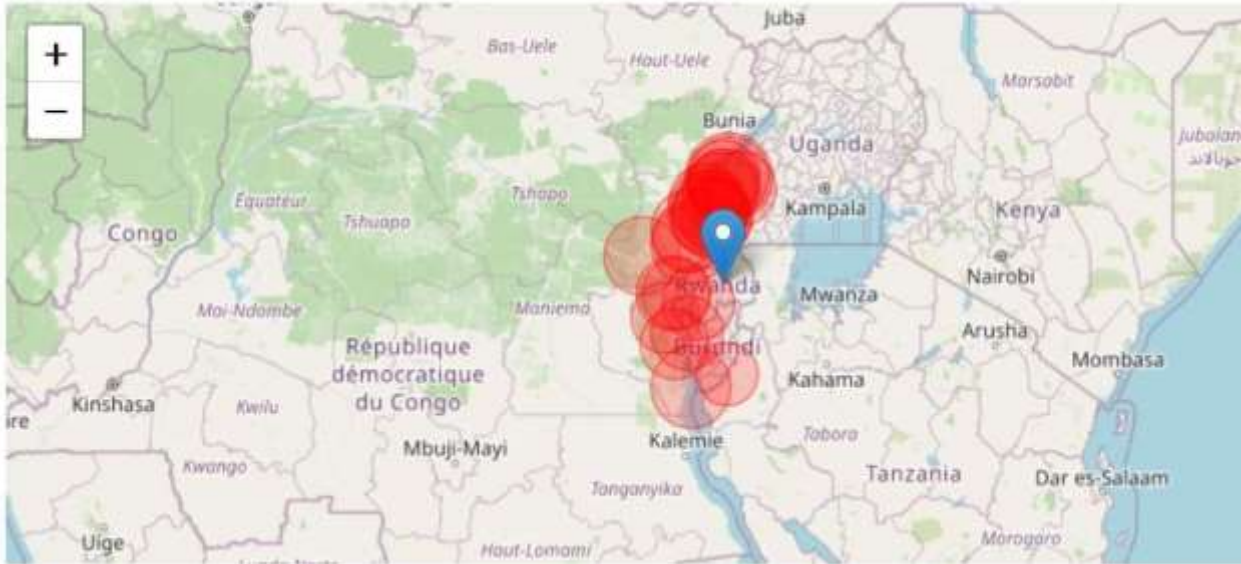


Figure 3: Map of latest earthquakes near Kigali.

The bar chart represents the yearly occurrence of earthquakes with a magnitude of 4 or above within 300 km of Kigali from 2015 to 2025. Over the past decade, a total of 107 earthquakes were recorded, averaging 10 earthquakes per year. However, there were significant fluctuations in seismic activity over the years. The most notable spike occurred in 2021, with 34 recorded earthquakes, making it the most seismically active year in the dataset. The strongest earthquake that year reached a magnitude of 5.0.

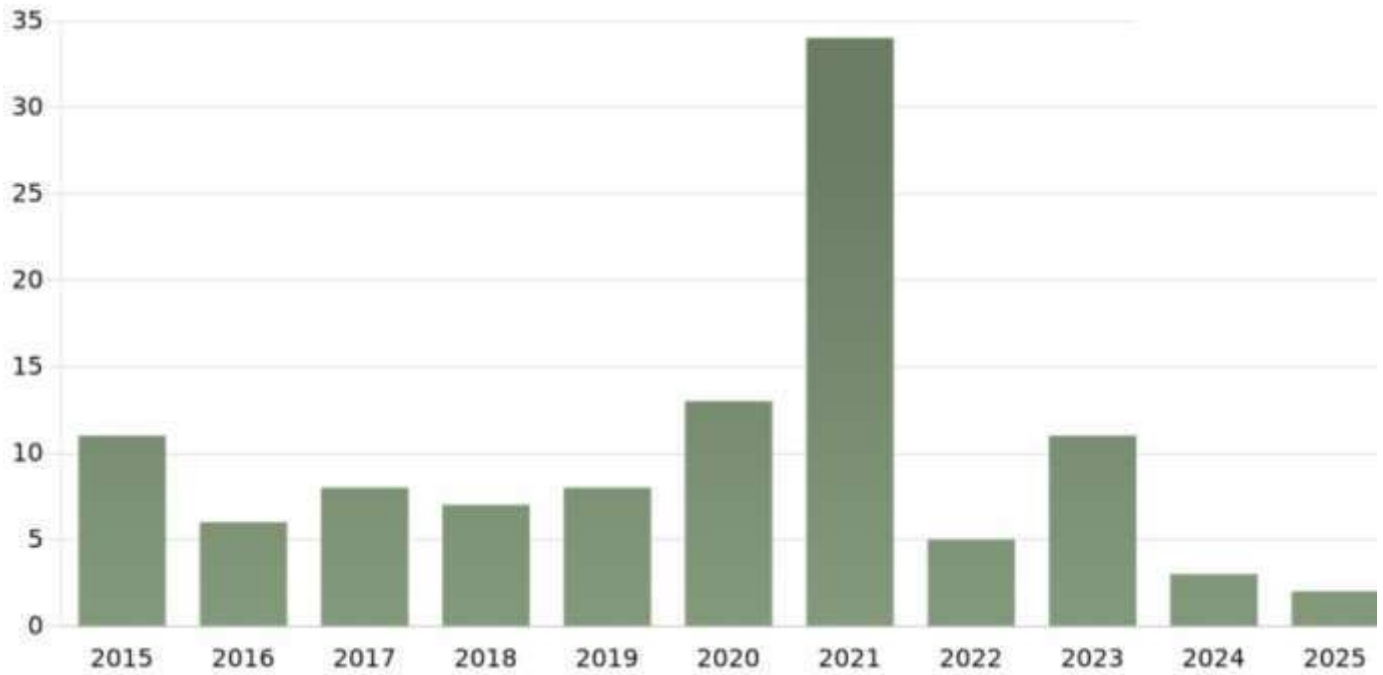


Figure 4: Earthquakes in 10 years

Apart from 2021, there were also relatively higher numbers of earthquakes in 2020 and 2023, with moderate increases in activity. However, the years 2022, 2024, and 2025 recorded significantly fewer earthquakes, suggesting a downward trend in seismic occurrences. The relatively high number of earthquakes in 2021 could indicate increased tectonic activity in the region, warranting further investigation into potential geological shifts (Manyena, S. B., Machingura, F, 2019).

The data suggests that while seismic activity is generally moderate in the Kigali region, occasional spikes can occur, emphasizing the importance of earthquake preparedness and monitoring. With a history of periodic increases in seismic events, authorities and residents should remain vigilant to mitigate potential risks from future earthquakes.

3.4 Data Preparation and Wrangling

In this study, multiple datasets from IoT sensors, GIS data sources, and meteorological agencies were collected and preprocessed to enhance urban disaster response. The datasets included real-time sensor readings for flood levels and earthquake vibrations collected. Additionally, GIS spatial data was incorporated for mapping disaster-prone areas. Since these datasets were recorded in different formats and time intervals, standardization and transformation were necessary for consistency. Data standardization and aggregation were essential for ensuring consistent and efficient analysis of flood

and earthquake data, which were recorded in real-time. The data was aggregated on both an hourly and daily basis to balance granularity with analysis efficiency. To address any missing data, particularly in time-series readings, interpolation techniques were applied. This method ensured smooth continuity in the dataset, effectively minimizing data loss and preserving the integrity of the analysis (Zhang, C., & You, F, 2020).

The processed datasets were merged into a unified dataset containing both disaster-related features and target variables. GIS spatial data was integrated with real-time sensor readings to enhance location based disaster risk analysis. Disaster severity was calculated by normalizing flood water levels and earthquake intensity relative to the affected population density. To facilitate machine learning-based classification, disaster risk levels were categorized as follows.

1. **Compute a risk threshold (r)** by analyzing the statistical range of disaster severity values.
2. **Define classification intervals:**
 - **Low Risk:** Interval1 = [min_risk, min_risk + r]
 - **High Risk:** Interval2 = [min_risk + 2r, max_risk]

A new categorical column, "**risk_level**," was added to the dataset, where:

- **0** represents Low disaster risk (Interval1).
- **1** represents High disaster risk (Interval2).

This structured data preparation process ensures accurate predictions, enhances real-time disaster monitoring, and supports GIS-based decision-making for urban disaster response.

3.5 Predictive Models Modelling

This section provides a detailed explanation of the various machine learning classification algorithms employed throughout this research. These algorithms are used to map the relationship between the dependent variables (model input) and independent variables (model target). The models implemented in this research include Logistic Regression, Random Forest Classifier, K-Nearest Neighbors (KNN) Classifier, Multi-Layer Perceptron (MLP) Classifier, Decision Tree Classifier, and Gradient Boosting Classifier. These algorithms were specifically chosen for their popularity in solving classification problems and the availability of extensive documentation, as they are widely used by the machine learning community. Each algorithm has its unique strengths and is selected

based on the nature of the data and the problem being addressed. Random Forest Classifier is chosen for its ability to handle noisy, incomplete data, reduce overfitting, provide feature importance, and offer accurate, scalable real-time predictions, making it ideal for urban disaster response.

3.5.1 Random Forest Classifier

The Random Forest Classifier is an ensemble learning method that improves upon individual decision trees by reducing their high variance and increasing model accuracy. Decision trees, while powerful for classification tasks, can suffer from overfitting, particularly when they are too complex and closely fitted to the training data. This overfitting leads to poor generalization on new, unseen data. Random Forest addresses this issue by constructing a forest of decision trees, each built using a random subset of the training data and a random subset of features. This diversity between the trees helps reduce overfitting and increases the robustness of the model (Alkassasbeh, M., Alkasassbeh, H., & Omar, K, 2021).

In the Random Forest algorithm, each tree in the forest is trained using a bootstrapped sample (random sample with replacement) of the data. Additionally, when constructing each decision tree, only a random subset of the available features is considered at each split, ensuring that the trees are less correlated with each other. By introducing these variations in both the data samples and features, Random Forest creates a diverse set of trees, each with its unique view of the data (Alsuhibany, S. A., Ahmad, I., & Mahmud, I, 2023).

Once all the trees are trained, the Random Forest Classifier aggregates the predictions of the individual trees to make the final decision. For classification tasks, this is typically done using a majority voting scheme, where the class that appears most frequently among the trees' predictions is chosen as the final output. This ensemble approach helps reduce the bias of individual trees while minimizing the variance, leading to a more accurate and stable prediction. Random Forest's ability to handle large, complex datasets produced by IoT sensors in flood and earthquake detection allows for robust predictions even when there are missing or noisy data points (Khan, M. A., Shah, J. H., & Iqbal, M. A., 2022).

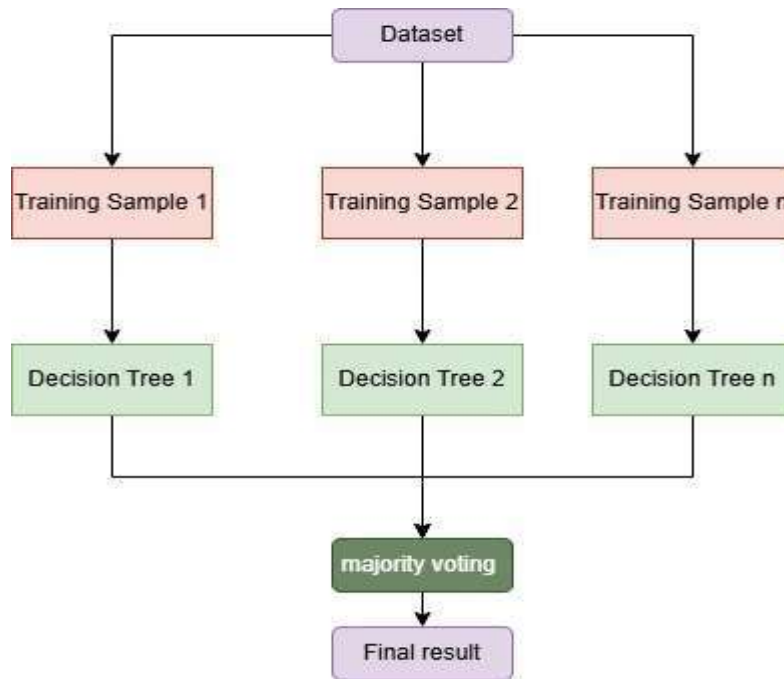


Figure 5: Building Random Forest Algorithm

3.6 Model Training and Evaluation

3.6.1 Features Selection

Feature engineering is a critical technique for enhancing the performance of machine learning models. As part of feature engineering, feature learning (or representation learning) is used to derive new features from the existing dataset. This technique helps in identifying the most relevant attributes for model training, improving accuracy and efficiency. For this research, before using the full set of features in the dataset, Decision Tree machine learning algorithms were applied to select the most important features for predicting disaster-related events like flood and earthquake occurrences in Kigali city. The primary predictors in this study included flood water levels and earthquake vibrations.

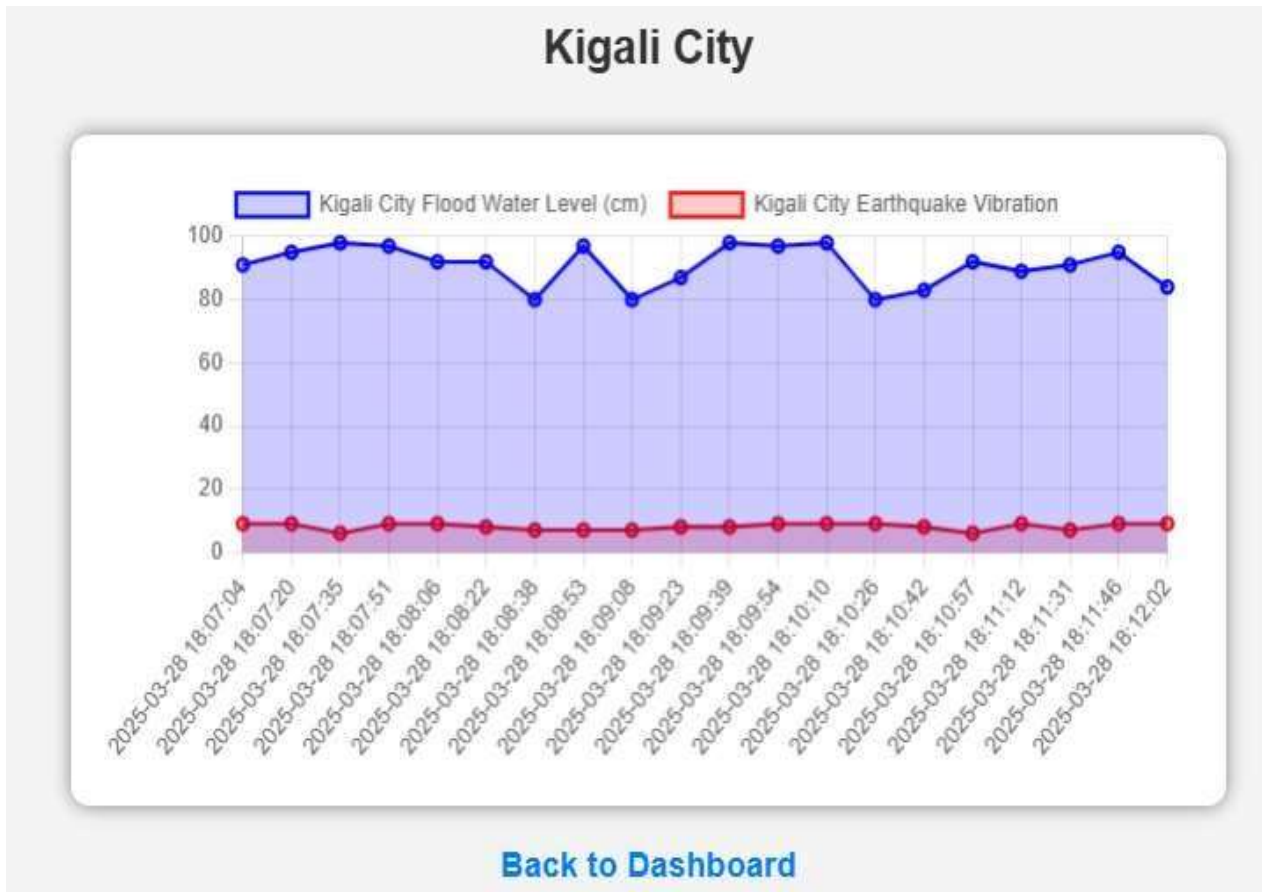


Figure 6: Kigali data selection

In the context of Kigali, the key predictors considered during training and evaluation were flood water levels and earthquake vibrations. These features were selected for their potential impact on disaster dynamics, which are crucial for urban disaster management.

3.6.2 Model training and Evaluation

In this research, the model training process involves using real-time data from IoT sensors, specifically focusing on flood water levels and earthquake vibrations, to predict disaster-related events in Kigali city. The dataset used for model training contains a total of 1200 samples, each consisting of several features, such as flood water levels, earthquake vibration intensity, and environmental factors. The target variable, "class," represents the specific disaster event classification, such as flood severity or earthquake magnitude.

To ensure effective model training and evaluation, the dataset was split into two subsets: the training dataset and the testing dataset. The training dataset contains 80% of the original dataset, while the

testing dataset holds the remaining 20%. Both datasets consist of input features flood water levels, earthquake vibrations. The target variable ("class"). This split allows for the effective training of the model while evaluating its generalization capabilities.

The training dataset is used to train machine learning models, Random Forest. This model learn patterns from the input features and predict the occurrence or severity of disaster events. The testing dataset, however, is used to evaluate the trained model and check for overfitting or under fitting. Overfitting occurs when a model performs well on the training data but fails to generalize to new, unseen data. The testing dataset helps identify whether the model is overfitting by assessing its performance on data it has not encountered during training.

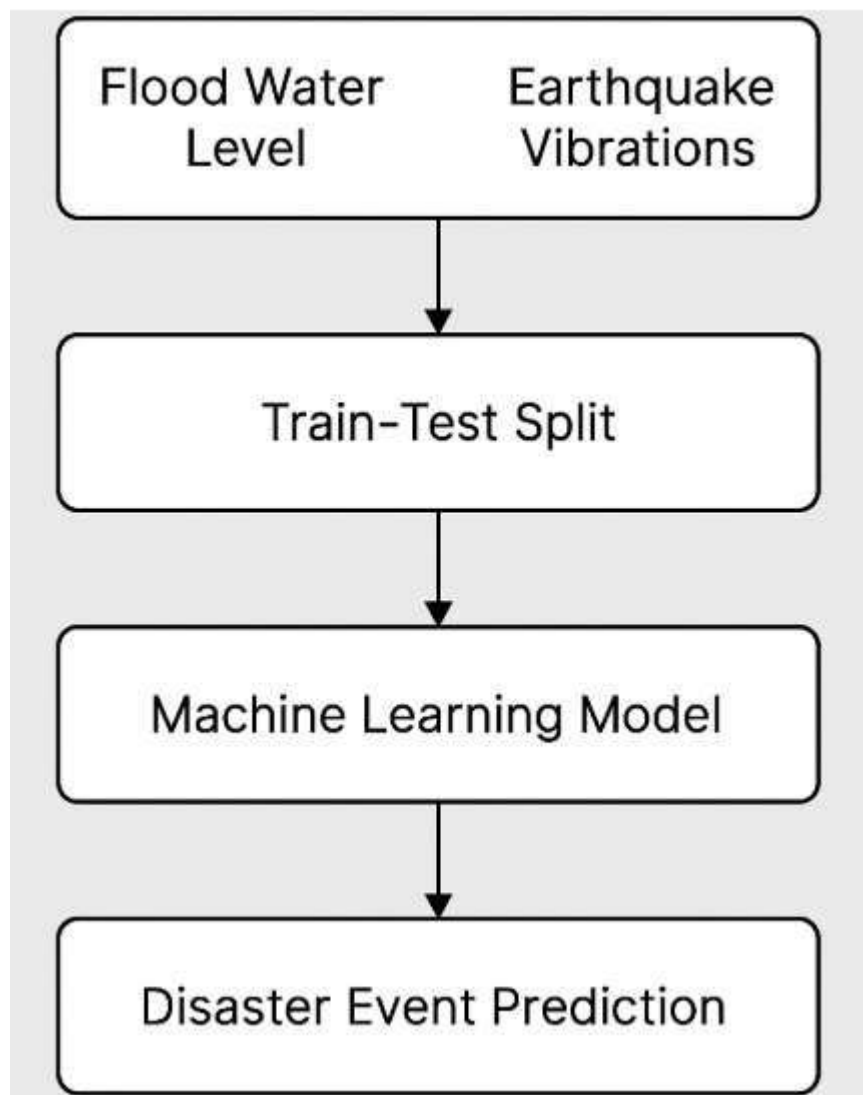


Figure 7: Machine Learning Training and Evaluation Process

After preparing the dataset for Machine Learning, the Random Forest classifier was trained to analyze the relationship between flood water levels, earthquake vibrations, and disaster occurrence patterns.

The implementation was carried out using Python, which was chosen for its stability, flexibility, and extensive library support for AI development, deployment, and maintenance.

Finally, the trained Random Forest model was evaluated to determine its effectiveness in predicting disaster events. Evaluation metrics such as predictive accuracy, precision, and recall were used to assess its performance. Prediction accuracy measures how well the model aligns with actual disaster occurrences, with higher accuracy indicating better performance in real-world disaster response scenarios.

3.6.3 Design Real Time Data Collection System

The real-time data collection system in this study is designed to monitor disaster-related parameters using IoT sensors. The system includes an ultrasonic sensor to measure flood water levels and a vibration sensor to detect earthquake activity. These sensors continuously gather data, which is critical for disaster prediction and response.

A NodeMCU (ESP8266) microcontroller is used to process sensor readings and transmit them to an IoT cloud platform via an internet-based network. This setup ensures continuous monitoring, real-time data availability, and early warning alerts for disaster management in Kigali, improving decisionmaking and urban safety.

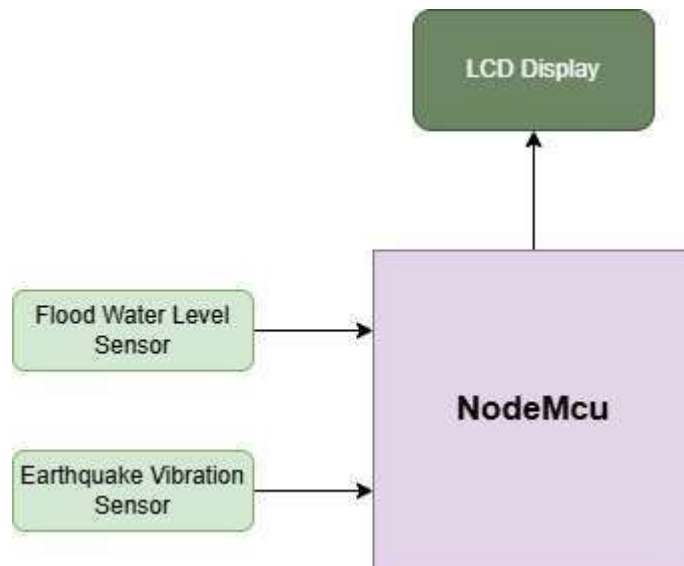


Figure 8: Data collection from sensor

The collected data from the Flood Water Level Sensor and Earthquake Vibration Sensor is transmitted via WiFi from the NodeMCU microcontroller to an MQTT Broker. The MQTT Broker acts as an intermediate communication channel, enabling efficient data exchange between the sensing system and the database at low power consumption. The data is then stored in a database, where it is processed using Python scripts and analyzed by the Machine Learning Model. The processed results are displayed on a system dashboard, accessible via a PC or web application user interface through WiFi. Additionally, real-time data is shown on an LCD display for instant monitoring.

This system ensures seamless integration between IoT sensors, data processing, and machine learning-based disaster prediction, improving disaster response efficiency.

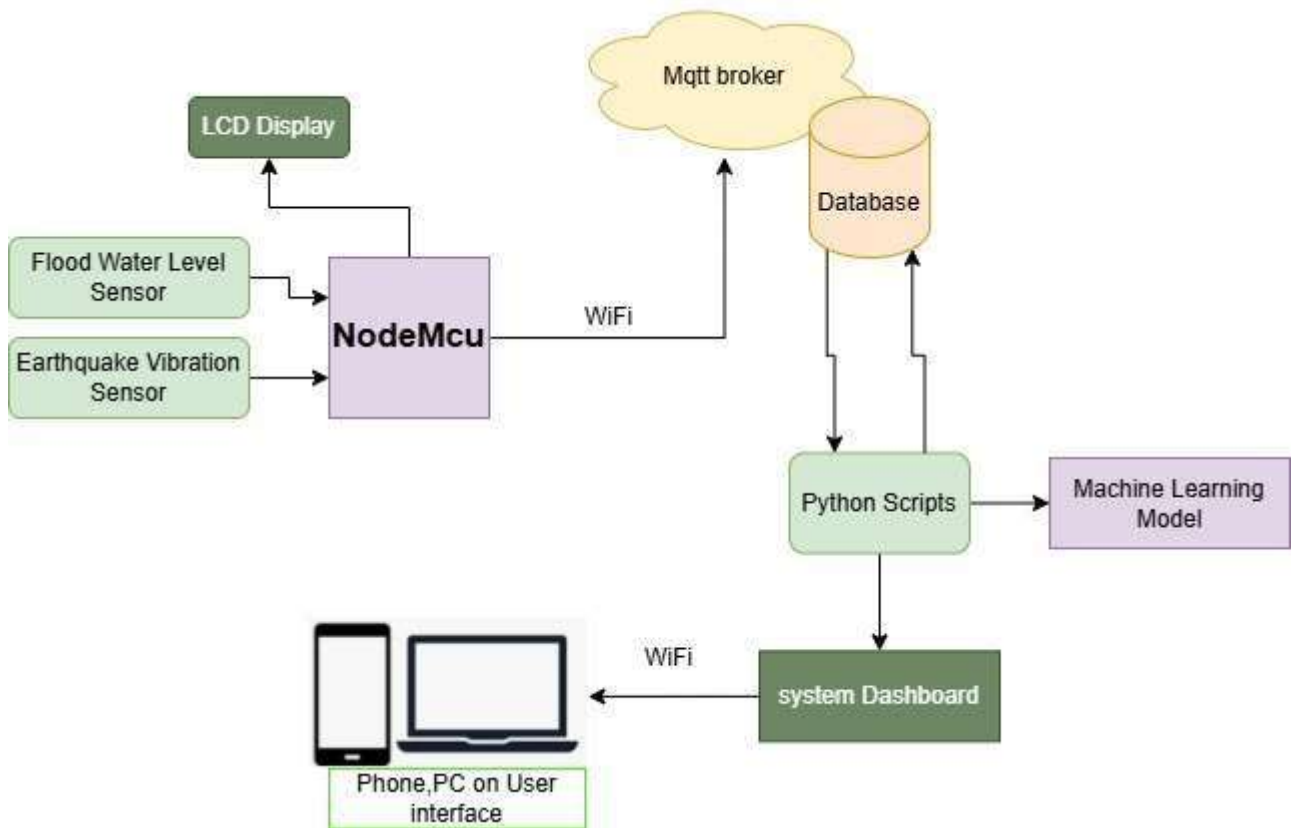


Figure 9: Real time data collection diagram

On the other side of the MQTT Broker, a server-side application was implemented using Python scripts to subscribe to the same topic as the publishing NodeMCU. The server processes the incoming sensor data from the Flood Water Level Sensor and Earthquake Vibration Sensor and stores it in a database for further analysis. The stored data is then analyzed using a Machine Learning Model, which helps predict potential disaster risks. The processed results are displayed on a system dashboard, accessible

via PCs and web application devices over WiFi. The figure above illustrates the system's real-time data flow, from IoT sensors to the dashboard for visualization and decision-making.

CHAPTER 4: SYSTEM ANALYSIS AND DESIGN

4.1 Introduction

During of the implementation of this research study project, different hardware and software components have been used. Thus, chapter gives a brief description on the architecture of the system implemented throughout this study. It gives also the details about the proposed simulation including simulation parameters and simulation scenarios. The system architecture used contains 5 subsystems. These include sensing part, wireless communication subsystem, user interface and database subsystem. The following paragraphs describe separately each subsystem in details.

4.2 Sensing Subsystem

The sensing subsystem consists of an ultrasonic sensor, an accelerometer, and a NodeMCU microcontroller. These components work together to collect essential environmental and movement data. The ultrasonic sensor is used for water level of flood, while the earthquakes. The NodeMCU processes the sensor readings and facilitates data transmission for further analysis.

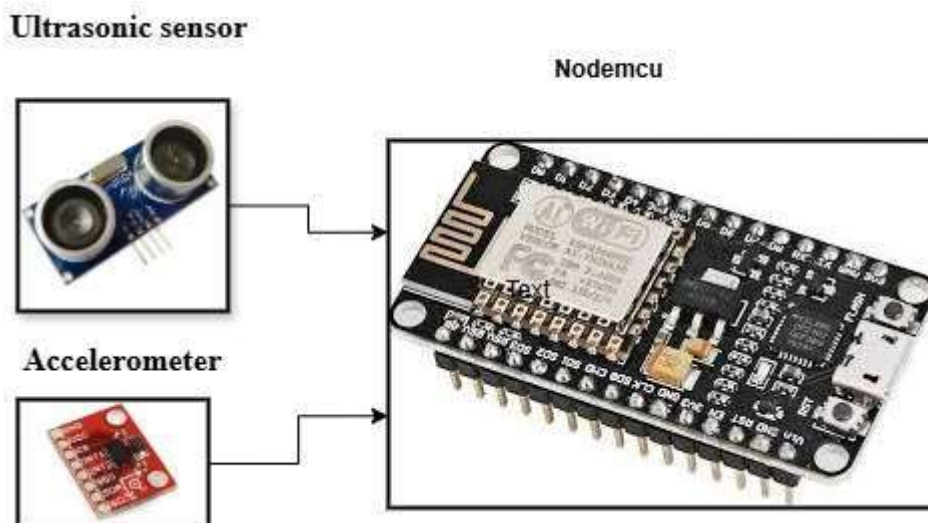


Figure 10: Sensing part on hardware

4.2.1 NodeMCU ESP8266 wi-fi internet development board

In this study, the design incorporates the NodeMCU Microcontroller. A microcontroller, as the term implies, is a compact integrated system that governs the functioning of embedded systems. It comprises a processor, memory, and various peripherals that facilitate interaction with the external environment. The NodeMCU ESP8266 Wi-Fi development board is an open-source platform and development kit

that enables the creation of IoT applications using Arduino code, making it an ideal choice for rapid prototyping of IoT products.



Figure 11: NodeMCU ESP8266 WIFI Internet Development Board

The best way to develop quickly an IoT application with less Integrated circuits to add is to choose this circuit “NodeMCU”. Today, we give a detailed Introduction on NodeMCU V3. It is an open-source firmware and development kit that plays a vital role in designing a proper IoT product using a few script lines. The module is mainly based on ESP8266 that is a low-cost Wi-Fi microchip incorporating both a full TCP/IP stack and microcontroller capability. The ESP8266 NodeMcu is a complex device, which combines some features of the ordinary Arduino board with the possibility of connecting to the internet. Arduino Modules and Microcontrollers have always been a great choice to incorporate automation into the relevant project. But these modules come with a little drawback as they don’t feature a built-in WiFi capability, subsequently, we need to add external WiFi protocol into these devices to make them compatible with the internet channel. This is the famous NodeMCU which is based on ESP8266 WiFi SoC. This is version 3 and it is based on ESP-12E (An ESP8266 based WiFi module). NodeMCU is also an open-source firmware and development kit that helps you to prototype your IOT product within a few LUA script lines, and of course you can always program it with Arduino IDE. In this article, we try present useful details related to this WiFi Development Kit, its main features, pinout and everything we need to know about this module and the application domain. Multiple GPIO pins on the board allow us to connect the board with other peripherals and are capable of generating PWM, I2C, SPI, and UART serial communications. The interface of the module is mainly divided into two parts including both Firmware and Hardware where former runs on the ESP8266 WiFi SoC and later is based on the ESP-12 module. The firmware is based on Lua – A scripting language that is easy to learn, giving a simple

programming environment layered with a fast scripting language that connects you with a well-known developer community.

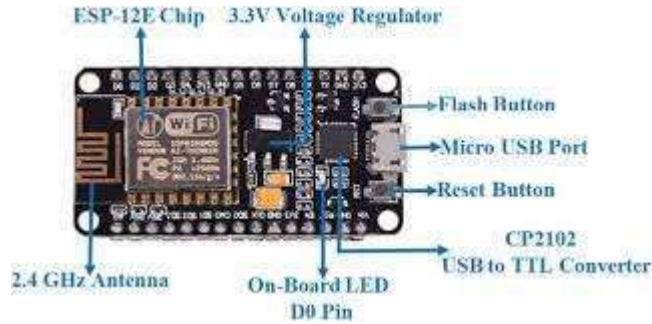


Figure 12: Main parts of NodeMCU

The open-source firmware provides the flexibility to modify, customize, and reconfigure the existing module, allowing for continuous adjustments to the interface until it meets your specific requirements. A USB to UART converter is included on the module to facilitate the conversion of USB data into UART data, which is the standard for serial communication. Instead of a traditional USB port, the module features a MicroUSB port, which serves a dual purpose: it allows for both programming the board and powering it. The board also includes a status LED, which blinks and then turns off quickly, providing real-time feedback on whether the module is functioning correctly when connected to the computer. The module’s ability to seamlessly establish a Wi-Fi connection between two channels makes it an excellent choice for integration with other embedded systems.

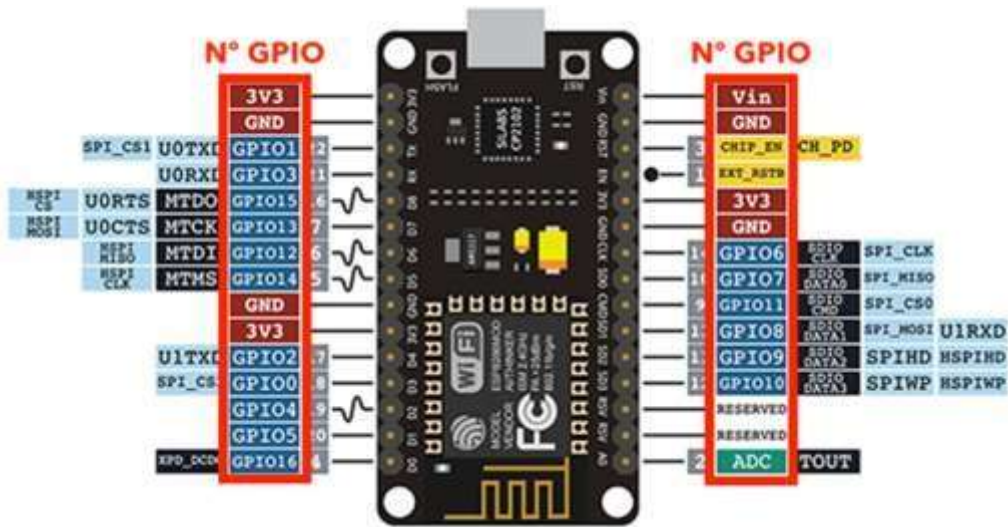


Figure 13: Pins of NodeMCU

NodeMCU V3 Pinout NodeMCU V3 comes with a number of GPIO Pins. Following figure shows the Pinout of the board. There is a candid difference between VIN and VU where former is the regulated

voltage that may stand somewhere 7 to 12 V while later is the power voltage for USB that must be kept around 5 V.

4.2.2 Ultrasonic sensor

The ultrasonic sensor works on the principle of sonar and radar system which is used to determine the distance to an object. An ultrasonic sensor generates high-frequency sound (ultrasound) waves. When this ultrasound hits the object, it reflects as echo which is sensed by the receiver as shown in below figure.

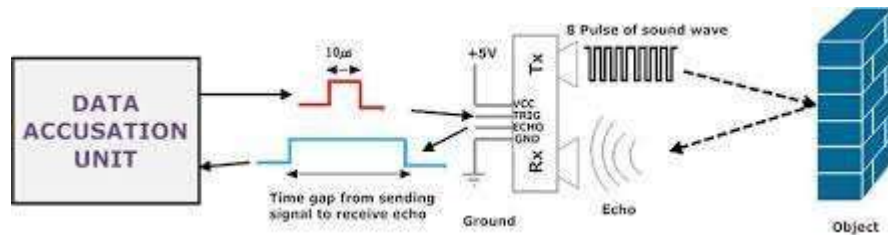


Figure 14: Ultrasonic Sensor Working Principle

By measuring the time required for the echo to reach to the receiver, we can calculate the distance. This is the basic working principle of Ultrasonic module to measure distance.



Figure 15: Ultrasonic Module

In the HC-SR04 ultrasonic module, a trigger pulse is sent to initiate the generation of ultrasound at a frequency of 40 kHz. Once the ultrasound is emitted, the module sends out 8 pulses at 40 kHz, after which it sets the echo pin high. This pin stays high until the reflected sound wave returns. The duration for which the echo pin remains high represents the time it takes for the sound wave to travel to the object and back. By measuring this time, we can calculate the distance to the object, knowing the speed of sound.

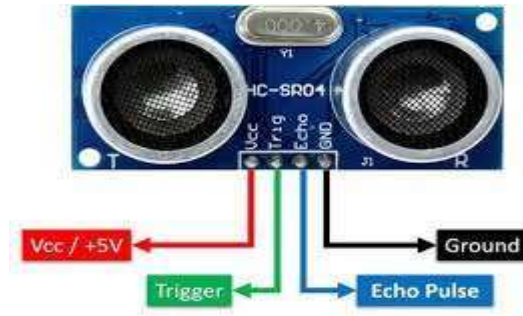


Figure 16: HC-SR04 Pin Diagram

4.2.3 Accelerometer Device

An accelerometer is a device that measures the vibration, or acceleration of motion, of a structure. The force caused by vibration or a change in motion (acceleration) causes the mass to “squeeze” the piezoelectric material which produces an electrical charge that is proportional to the force exerted upon it. Since the charge is proportional to the force, and the mass is constant, then the charge is also proportional to the acceleration. These sensors are used in a variety of ways from space stations to handheld devices – and there’s a good chance you already own a device with an accelerometer in it. For example, almost all smartphones today house an accelerometer. They help the phone know whether it undergoes acceleration in any direction, and it’s the reason why your phone’s display switches on when you flip it. In an industrial setting, accelerometers help engineers understand a machine’s stability and enable them to monitor for any unwanted forces/vibrations.

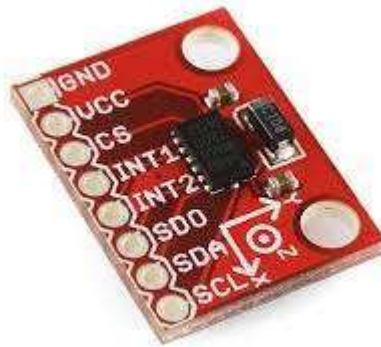


Figure 17: Accelerometer device

An accelerometer is a device designed to measure both static and dynamic acceleration, making it useful for earthquake detection. Static acceleration includes constant forces gravity, while dynamic acceleration refers to non-uniform forces, vibrations or shocks, which are characteristic of earthquakes. The sensor detects these accelerations and converts them into electrical signals. There are several types of accelerometers, each with distinct working principles. Piezoelectric accelerometers generate

electrical signals when a seismic weight applies force to a piezoelectric crystal, making them ideal for measuring shocks and vibrations, including those caused by earthquakes. Piezo resistive accelerometers change resistance based on acceleration and are commonly used in high-amplitude applications earthquake monitoring. Capacitive accelerometers measure changes in capacitance as the diaphragm alters the distance between capacitive plates, and they are used in many consumer devices like smartphones, which can detect tremors. Triaxle accelerometers measure acceleration in three perpendicular directions, offering a comprehensive analysis of vibrations, which is crucial for detecting the full impact of seismic activity. Accelerometers are increasingly used in earthquake monitoring systems to measure vibrations from seismic events. They can trigger early warning systems, measure the intensity of earthquakes, and monitor the stability of structures during seismic events. Overall, accelerometers play a critical role in earthquake detection and analysis, contributing to safety and disaster preparedness.

4.3 Wireless Communication system

This IoT system enables real-time data collection, transmission, and monitoring using NodeMCU, a microcontroller equipped with a Wi-Fi module. NodeMCU gathers data from connected sensors and transmits it wirelessly over a Wi-Fi network. The collected data is sent to an MQTT broker, which acts as an intermediary, efficiently distributing the data to various endpoints. One key destination is a SQL database, where the data is securely stored for future retrieval and analysis. Additionally, the data is forwarded to a cloud/server, where it undergoes processing, visualization, and further analysis. This architecture ensures seamless communication, continuous monitoring, and real-time decision-making, making it highly suitable for applications such as smart homes, industrial automation, and environmental monitoring.

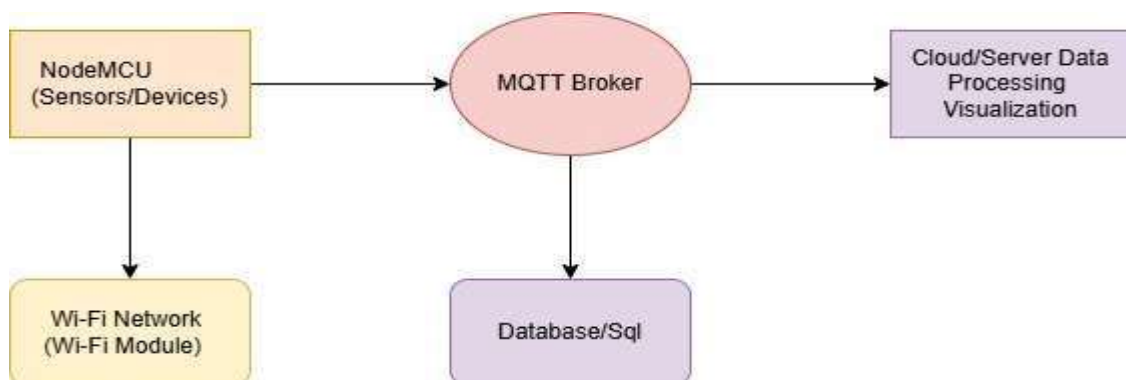


Figure 18: Block diagram of Communication system

Ultrasonic sensors detect flood water level, while accelerometers track earthquakes, helping assess potential risks like earthquakes. The NodeMCU microcontroller collects sensor data and transmits it via Wi-Fi to an MQTT broker, which relays the information to an SQL database for storage and analysis. GIS platforms visualize real-time data, helping authorities monitor disaster-prone areas.

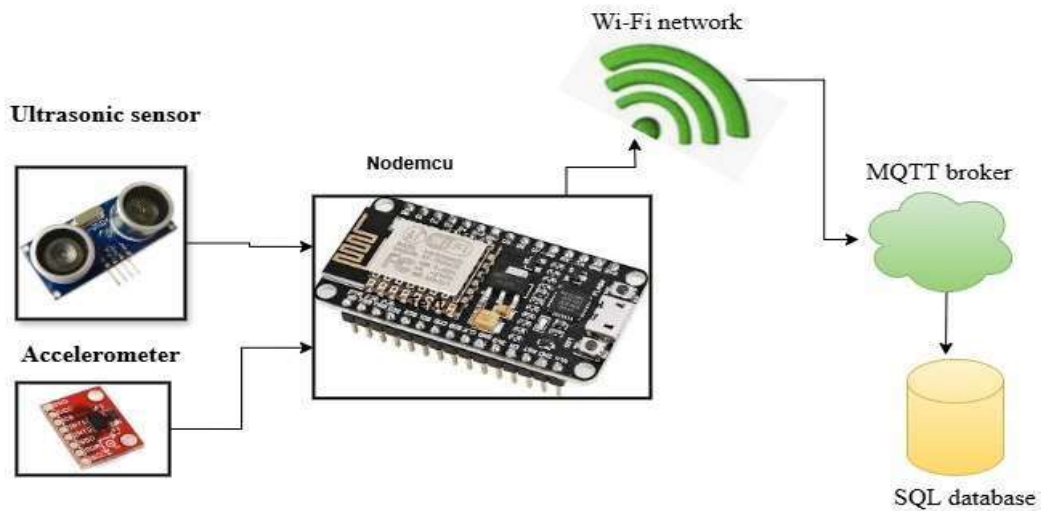


Figure 19: Wireless Communication system on hardware

The System User Interface Subsystem connects the database, backend, ML model, and dashboard for enhanced urban disaster response. The SQL database stores disaster-related data, which the PHP backend processes and forwards to the ML model for analysis. The model analysis disaster patterns and sends insights back to the backend. The dashboard provides a real-time interface for emergency responders and authorities, displaying alerts, GIS maps, and analytics. This integration enables quick decision-making, improving disaster response efficiency. The PHP backend ensures smooth communication, while the ML model enhances forecasting accuracy.

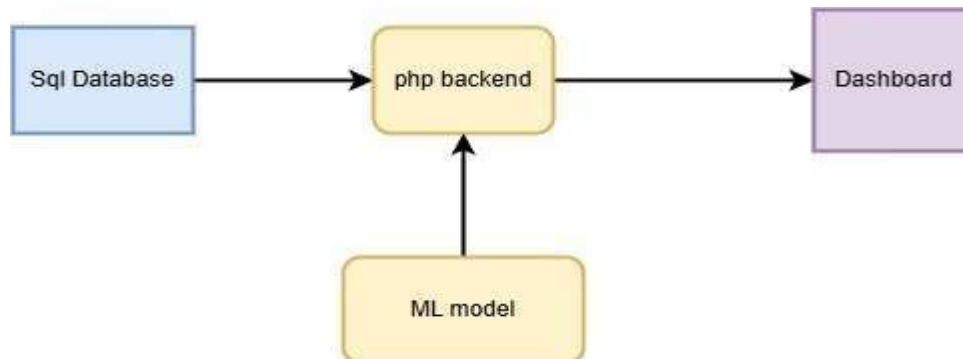


Figure 20: Block diagram of user interface

CHAPTER 5: RESULTS AND ANALYSIS

5.1 Introduction

This chapter presents the implementation and performance evaluation of the real-time disaster monitoring system developed to detect early indicators of natural disasters such as floods and earthquakes. The system uses sensors to collect flood water level and seismic vibration data, which are analyzed and displayed on a cloud-connected dashboard. A machine learning model is integrated to classify conditions as normal or abnormal and to predict potential disasters based on historical trends and real-time data. This enhances the system's ability to generate timely alerts and enables proactive emergency response, ultimately improving disaster preparedness and risk reduction.

The starting user interface of the disaster monitoring system is a login page that ensures only authorized users can access the platform. It consists of a username and password input field, where users enter their credentials. Once entered, clicking the "Login" button submits the data for authentication. If valid, users gain access to the system dashboard; otherwise, they receive an error message. This login interface enhances security by preventing unauthorized access to critical disaster data.



Figure 21: Login interface

The Real-Time Disaster Monitoring Dashboard is a user-friendly platform designed to track and analyze disaster-related sensor data efficiently. We have two graphs, one for monitoring flood water levels and another for earthquake vibrations, providing real-time insights into environmental changes. Additionally, a sensor readings panel displays the latest data, including flood levels, earthquake intensity, and a location link for geographical reference. Users can also access detailed reports for further analysis.

The result on the dashboard displays real-time sensor readings including a flood water level of 77 cm and an earthquake vibration of 4. The system status is labeled as “Normal.” It also provides a Google Maps location, links to view detailed reports, and specific data related to Kigali.

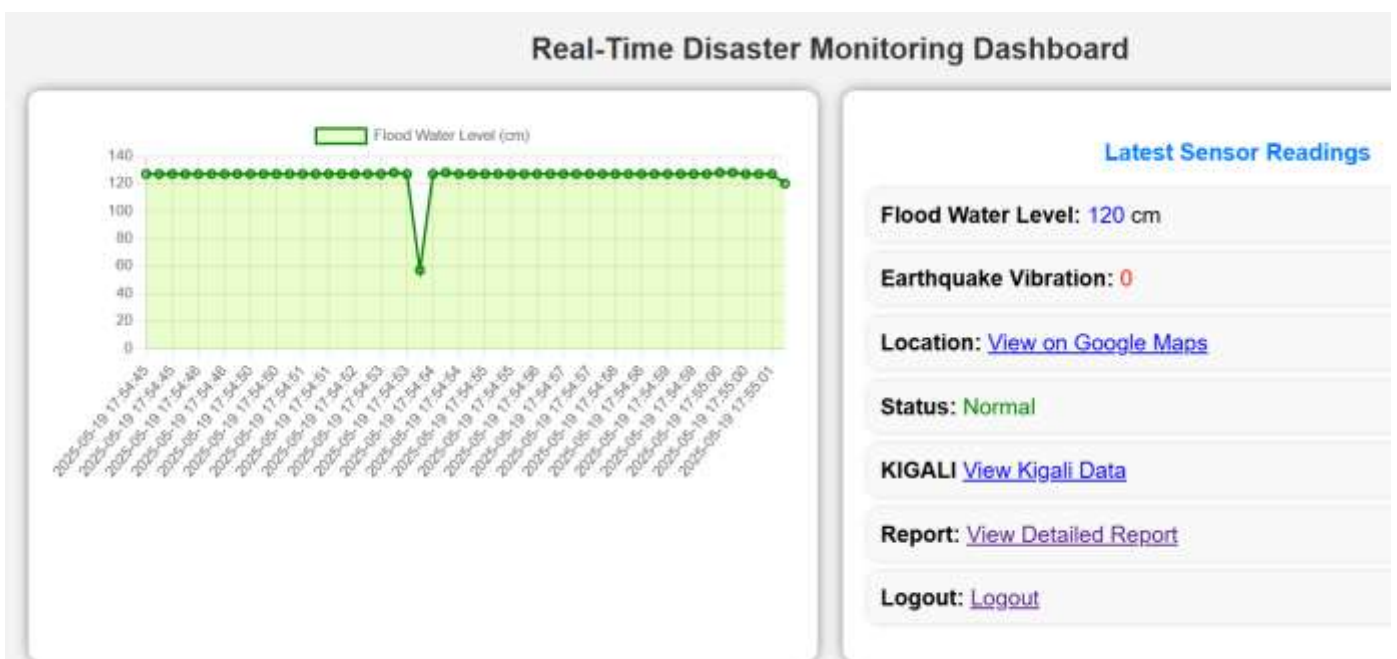


Figure 22: Normal Result on dashboard

This dashboard displays real-time disaster data for Kigali. It shows a flood water level of 134 cm and earthquake vibration of 8, indicating abnormal conditions. A chart tracks flood trends over time. Links provide access to location, detailed reports, and data for further analysis or emergency response.



Figure 23: Abnormal Result on dashboard

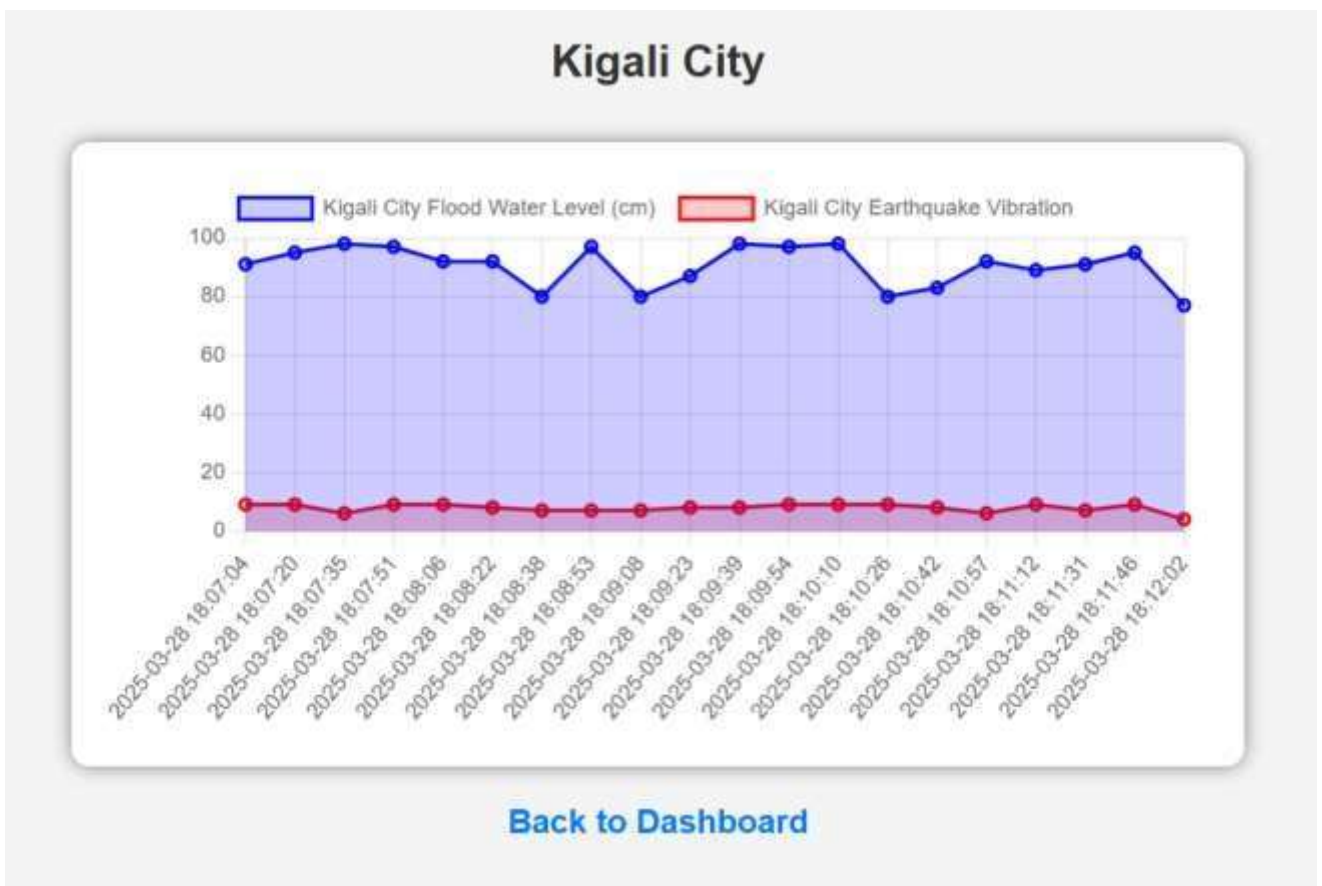


Figure 24: Flood water level and Earthquake on the same Graph

The Disaster Monitoring Report provides real-time sensor data on flood levels and earthquake vibrations. It includes a timestamp for tracking when data was recorded, flood water level to monitor rising or falling water levels, and earthquake vibration values indicating seismic activity. This report helps emergency responders analyze trends and take action. Users can review past readings for better

decision-making. A "Back to Dashboard" link allows quick navigation to the main monitoring interface for real-time updates.



Figure 25: Alert Notification

The alert feature sends real-time SMS notifications when abnormal flood levels or earthquake vibrations are detected in Kigali. It monitors sensor data continuously and triggers alerts when safety thresholds are exceeded. Flood alerts indicate rising water levels, while vibration alerts warn of possible seismic activity. Each message includes the alert type, location, and value to help users understand the risk level. This one-way alert system enables quick awareness, helping residents and emergency responders take timely action to minimize disaster impact.

Disaster Monitoring Report

Timestamp	Flood Water Level (cm)	Earthquake Vibration	Status
2025-05-19 17:55:04	20 cm	0	Normal
2025-05-19 17:55:01	26 cm	0	Normal
2025-05-19 17:55:01	127 cm	0	Abnormal (Flood Level High)
2025-05-19 17:55:00	127 cm	0	Abnormal (Flood Level High)
2025-05-19 17:55:00	78 cm	0	Normal
2025-05-19 17:55:00	128 cm	0	Abnormal (Flood Level High)
2025-05-19 17:55:00	93 cm	0	Normal
2025-05-19 17:54:59	34 cm	0	Normal
2025-05-19 17:54:59	127 cm	0	Abnormal (Flood Level High)
2025-05-19 17:54:59	127 cm	0	Abnormal (Flood Level High)

Figure 26: Report user interface



Figure 27: Hardware prototype

This image shows a functional hardware prototype of an IoT-based disaster monitoring system. It includes an LCD screen that displays real-time environmental data collected from connected sensors. The reading "Flood: 30 Cm" indicates the current water level detected by a flood sensor, while "Vib: 4" shows the earthquake vibration intensity, possibly measured using a vibration or accelerometer sensor. The system is likely powered by a microcontroller such as Arduino or ESP8266. This setup

plays a key role in early disaster detection, providing immediate feedback on local conditions. When integrated with a cloud platform or dashboard, it enables remote monitoring, data analysis, and timely alerts for disaster response teams, improving public safety and preparedness in flood- and earthquake prone areas like Kigali.

CHAPTER 6: CONCLUSION AND RECOMMENDATION

6.1 Conclusion

This project successfully designed and implemented an integrated IoT-GIS-based emergency management system focused on optimizing urban disaster response in Kigali City. The system leverages real-time data from flood water level sensors and earthquake vibration sensors, visualized through a user-friendly web-based dashboard. Key components included IoT-enabled data acquisition, geolocation capabilities, cloud-based storage, and real-time visualization.

The implementation demonstrated how real-time environmental data could be gathered, analyzed, and presented to assist in timely and informed decision-making. By providing continuous monitoring and automatic updates every few seconds, the system addresses the challenges of delayed or inadequate disaster response in rapidly growing urban environments like Kigali.

Furthermore, the use of GIS mapping through geolocation ensures that local authorities and responders can pinpoint areas affected by potential disasters, enhancing situational awareness. While machine learning integration was conceptualized in this phase, its implementation remains an area for future extension, where patterns in sensor data could be used for predictive analytics and early warnings.

6.1 Recommendation

To enhance the effectiveness and scalability of the integrated IoT-GIS-based emergency management system in Kigali City, it is recommended to collaborate with the African Center of Excellence in Internet of Things (ACEIoT) at the University of Rwanda (UR), whose research capacity and infrastructure can support further development and deployment. Additionally, the system should be expanded to monitor other hazards such as landslides, fires, and air pollution for broader disaster coverage. Engaging local communities in Kigali City through awareness and training ensure grassroots-level responsiveness. Integration with national disaster management systems can improve coordination and facilitate real-time decision-making. To maintain operational reliability, solar powered sensor nodes and redundant communication networks should be considered for power and connectivity resilience. Lastly, regular maintenance and calibration of sensors are essential for long term accuracy and system performance.

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