AN EMBEDDED AND MACHINE LEARNING BASED EARLY FLOOD MONITORING AND WARNING SYSTEM : A CASE OF RIVER MANAFWA

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Abstract

Flooding remains a serious threat in many parts of Uganda, especially in regions with limited access to early warning systems. This project introduces a practical solution that combines embedded hardware and machine learning to monitor and predict flood events in real time. Using a flow sensor and an ultrasonic sensor connected to an ESP32 device, the system captures data on water movement and levels. These readings are automatically logged to Google Sheets, allowing for easy data management and access. A backend built with FastAPI processes this information, using a trained Random Forest algorithm to forecast potential flood risks. The results, along with past records, are displayed on an interactive dashboard developed in React. By merging simple electronics with predictive analytics, the system provides an affordable and adaptable tool to support timely flood response efforts in vulnerable areas.

GitHub link to project:

`https://github.com/dwavah/FloodProject.git`

Declaration

I, Wavamunno Daniel Lukyamuzi, solemnly declare that the content presented in this report is the outcome of my own independent efforts, research and critical analysis. I have compiled and structured this document with the utmost integrity, drawing upon credible and verifiable sources available to me as of 17th April 2025.

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APPROVAL

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Acknowledgement

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Chapter 1

INTRODUCTION

Flooding has increasingly become a matter of global concern, primarily due to the scale of destruction it brings to both human life and the economy. Among natural disasters, floods stand out as particularly deadly, often surpassing the impacts of tsunamis, earthquakes, and volcanic eruptions. Over the course of the 20th century, flood events were linked to approximately 6.8 million fatalities. Notably, nearly half of these deaths occurred in Asia during the final 25 years of that century [1].

1.1 BACKGROUND

1.1.1 Global Perspective

One of the most catastrophic floods in Pakistan's history occurred when unprecedented monsoon rains triggered a deluge of historic proportions, inundating nearly a third of the nation. This tragic event affected over 33 million people, claimed the lives of more than 1,700 individuals, and resulted in estimated damages exceeding 30 billion US dollars. The consequences extended far beyond financial loss, with widespread displacement, severe soil degradation, and the destruction of key agricultural regions pushing the country toward a near-famine situation [2].

In the United States, floods rank among the most frequent and destructive natural events, consistently leading to significant human casualties, infrastructure loss, and economic disruption. Over the past decade alone, flooding has accounted for over 155 billion US dollars in property damage, making it the costliest natural hazard in the country each year. Several states face heightened vulnerability due to a combination of geographical features, climatic patterns, and long-standing land use practices that exacerbate flood risks [3].

1.1.2 Regional Perspective

The African continent has also experienced the harsh consequences of flooding, with many regions facing repeated disasters fueled by a combination of climate change, unplanned land development, and inadequate infrastructure. These flood events often result in tragic loss of life and place immense pressure on national economies.

One of the most tragic incidents in recent memory occurred in Libya in 2023, when Storm Daniel swept through the town of Derna. The resulting floods led to the deaths of more than 11,000 people, while thousands more were reported missing. The collapse of dams and critical infrastructure only worsened the catastrophe, making it one of the most fatal flood disasters on the continent that year [4].

In East Africa, since the onset of the long rains in March 2020, the region has endured severe and widespread flooding. Over 1.3 million individuals were affected, with at least 481,000 displaced across several countries. Kenya experienced major losses due to rising rivers and landslides, with nearly 200 fatalities and tens of thousands left homeless. Meanwhile, Uganda saw some of the worst flooding in decades, as Lake Victoria reached water levels not seen in over a century. This triggered flash floods that destroyed property and displaced large populations [5].

1.1.3 National Perspective

Uganda faced multiple severe flood events in 2023, with some of the most damaging occurring during the months of August and September. In Ntoroko District alone, heavy flooding led to widespread devastation, forcing more than 24,000 people to flee their homes and resulting in 23 confirmed fatalities by early September [6]. The destruction extended to homes, public infrastructure, schools, and healthcare facilities, leaving affected populations at heightened risk of diseases such as cholera.

Earlier in the year, from April to May, several districts including Kasese, Mbale, and Rukungiri were hit by flash floods and landslides, which tragically claimed over 40 lives during that period [7]. The impact of flooding continued into the final quarter of the year, with more than 79,000 individuals affected by El Niño-induced floods between October 1st and November 14th, as monitored through the Emergency Event Tracking (EET) system [8].

In Eastern Uganda, the Bududa District has also experienced repeated incidents of flooding and mudslides, with one of the worst resulting in the deaths of approximately 40 people [9]. In response to these recurring disasters, various measures have been adopted nationally, including the promotion of sustainable farming practices, improvement in community-level disaster preparedness, and the collaboration of both governmental bodies and non-governmental organizations to support flood resilience initiatives [10].

1.2 Statement of the Problem

Flooding remains one of the most frequent causes of both loss of life and large-scale displacement worldwide. Between 2010 and 2020, an estimated 255 million individuals were affected by flood events across the globe. Financially, the toll has been enormous, with economic damages surpassing 650 billion US dollars during that same period. Regions such as Asia and Sub-Saharan Africa have been highlighted as particularly vulnerable, largely due to dense populations and limited disaster response infrastructure [11].

In Uganda, flooding has presented persistent environmental and humanitarian challenges over the past ten years. The consequences have been far-reaching, disrupting livelihoods, damaging infrastructure, and straining the national economy. Uganda's natural geography—including an extensive network of rivers, lakes, and wetlands—makes it especially susceptible to flooding, particularly during periods of intense seasonal rainfall.

The growing threat of climate change has only intensified the situation, leading to shifts in weather patterns and longer durations of heavy rainfall. Recent studies suggest that Uganda is experiencing increasingly frequent and intense rainfall events, which continue to trigger floods in different parts of the country [12].

1.3 Objectives of the Study

1.3.1 General objective

This study aims at developing an embedded system and machine learning based flood monitoring and detection system that uses sensor technology that can benefit the people around River Manafwa region.

1.3.2 Specific objectives

- To investigate and analyse the problems caused by flooding in Bududa, Manafwa, Mbale and Butaleja districts (districts through which River Manafwa flows).
- To develop a system (prototype).
- To test and validate the system developed.

1.4 Research Questions

This study is guided by a set of questions that aim to explore how emerging technologies can be applied to the challenge of flood management in Uganda:

1. In what ways can embedded sensor systems be used to gather accurate, real-time flood data within localized environments?

2. Which machine learning approach can most effectively analyze sensor data to forecast potential flood risks?

3. How can integrating real-time data into an interactive web dashboard contribute to early warning and public awareness?
4. What challenges and benefits are associated with using Internet of Things (IoT) and artificial intelligence for flood prediction in Uganda?

1.5 Hypotheses

The research operates under the assumption that the integration of real-time data collection and predictive modelling can significantly improve flood monitoring and preparedness. The key assumptions are as follows:

- **Hypothesis One (H1).** A supervised learning model, particularly a Random Forest classifier, can be trained to identify and predict flood scenarios with a high degree of accuracy using sensor-generated data.
- **Hypothesis Two (H2).** A centralized dashboard that visualizes live sensor readings and prediction results will enhance the timeliness and efficiency of flood response efforts in targeted regions.

1.6 Scope of the Study

This research will center on the Manafwa River, situated in eastern Uganda and bordered by the districts of Bukedea, Bududa, Manafwa, Butaleja, and Mbale. The area has consistently faced flooding, especially during periods of intense rainfall, leading to widespread damage and hardship for local communities. Given its vulnerability and history of flood events, this region offers a valuable setting for exploring flood dynamics and assessing the potential of monitoring systems to mitigate risks.

The analysis will draw upon literature published over the past fifteen years, specifically from 2007 to 2022. This timeframe has been chosen as it captures recent developments and flood-related incidents within Uganda, providing a relevant foundation for addressing the study's core objectives.

1.7 Significance of the study

The ability to monitor floods and issue early warnings plays a crucial role in protecting lives and minimizing economic damage. By alerting communities before disaster strikes, many of the worst consequences can be avoided.

This research aims to add value to the existing body of knowledge surrounding flood monitoring and early warning systems, particularly within the context of developing nations such as Uganda. It highlights practical approaches that can be adapted to local conditions and needs.

Moreover, the findings of this study may serve as a foundation for future academic work. Researchers interested in exploring similar topics may find the insights presented here useful for developing a deeper understanding of flood management strategies.

Finally, it is essential that any flood monitoring solution developed is both practical and accessible. It should be easy to use by local residents living near the Manafwa River, as well as by the relevant authorities responsible for disaster response in the region.

1.8 Definition of Terms

To ensure clarity and consistency throughout the report, key terms are defined below as they apply within the scope of this research:

- **Embedded System.** A specialized computing system designed to perform dedicated functions within a larger mechanical or electrical system, often with real-time computing constraints.
- **ESP32.** A compact microcontroller with built-in Wi-Fi and Bluetooth capabilities, commonly used in IoT-based applications for wireless data transmission.
- **Ultrasonic Sensor.** A device that estimates the distance to an object or surface by emitting ultrasonic waves and measuring the time it takes for the echo to return.
- **Flow Sensor.** A sensor that quantifies the volume or rate of liquid moving through

a pipe or channel, used in this context to measure water flow.

- **IoT (Internet of Things).** A network of physical devices connected to the internet, capable of collecting, sending, and receiving data.
- **Random Forest.** An ensemble machine learning technique that builds multiple decision trees during training and merges their outputs for improved accuracy and robustness.
- **FastAPI.** A high-performance Python web framework used to develop APIs for data handling and machine learning inference.
- **Dashboard.** A graphical interface that consolidates and displays data metrics, system alerts, and analytics in real time for easier interpretation and decision-making.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

Floods continue to pose a significant threat across the globe, particularly in regions prone to heavy rainfall and inadequate drainage systems. Various countries have implemented diverse approaches to detect, monitor, and respond to flood events using modern technologies. This chapter examines selected systems currently in use around the world, ranging from sensor networks and satellite imaging to integrated data dashboards, and evaluates how these solutions inform the development of a flood monitoring and prediction system tailored to Uganda's context.

2.2 Review of Existing Systems and Approaches

2.2.1 Multi-Radar Multi-Sensor System in the United States

The United States developed the Multi-Radar Multi-Sensor (MRMS) system to enhance national flood forecasting and weather response. Operational since 2014, the MRMS integrates input from over 160 radar stations, environmental sensors, and advanced weather models. One of its main advantages is the high frequency of updates, occurring every two to five minutes, which allows meteorologists to deliver rapid and localized alerts—particularly vital for flash flood scenarios [13].

The MRMS leverages data from NEXRAD radar stations, satellite sources, and lightning detection systems to compile comprehensive precipitation maps. Its layered radar network provides redundancy and coverage in remote areas, improving the reliability of forecasts. As shown in Figure 5.1, MRMS is now fully deployed across all U.S. states and continues to support emergency preparedness by offering high-resolution and timely warnings to disaster response teams and communities.

2.2.2 Flood Early Warning Systems in Uganda

In response to persistent flooding in Butaleja District, the Ugandan government partnered with the International Telecommunication Union (ITU) to deploy solar-powered Flood Early Warning Systems. These systems consist of three key components: a river-side water-level sensor, a solar-powered siren, and a district control center equipped with backup monitoring infrastructure [14].

When the sensor detects that water levels have surpassed a critical threshold, the siren activates automatically and emits a loud alert audible within a 10-mile radius. Additionally, district authorities can broadcast pre-recorded voice instructions in English and the local language (Lunyole), guiding residents on evacuation procedures. The first of such installations was launched in 2014 at Namulo Bridge and has since served as a model for localized early warning initiatives in Uganda.

2.2.3 RISAT-1A Satellite Monitoring in India

India's flood surveillance strategy was significantly enhanced by the deployment of RISAT-1A, a synthetic aperture radar (SAR) satellite developed by the Indian Space Research Organisation (ISRO). Operational since 2022, RISAT-1A provides flood imagery through various acquisition modes, including ScanSAR and Stripmap, allowing authorities to tailor flood analysis based on resolution and area coverage [15].

A notable benefit of RISAT-1A is its ability to penetrate cloud cover and deliver real-time imagery during severe weather conditions. During the 2022 monsoon season, over 67 flood maps were generated using data from this satellite. This technology played a critical role in emergency coordination across flood-prone states such as Bihar and Kerala, improving evacuation procedures and disaster logistics.

2.2.4 GIS-Based Flood Mapping in South Africa

South Africa has adopted flood risk mapping as a proactive measure to identify and mitigate potential flood zones. These maps are generated through the use of geographic information systems (GIS), satellite imagery, and hydrological records, offering insights into terrain vulnerability, land use and climate patterns [5].

Legislative frameworks such as the Disaster Management Act (2002) mandate the development of flood hazard maps, which are routinely utilized by the South African Weather Service (SAWS). Academic institutions like Stellenbosch University have also contributed to advancing regional flood models. Despite challenges like limited data coverage, combining satellite analysis with hydraulic simulations has improved emergency readiness, particularly in high-risk regions like the Eastern Cape.

2.3 Review Mapped to Objectives

Each of the systems reviewed contributes to the overarching objective of improving flood monitoring and response. The MRMS system aligns with the goal of real-time data aggregation for early alerts. Uganda's local siren-based systems demonstrate how sensor-triggered alerts can support grassroots resilience. India's RISAT-1A satellite illustrates the power of remote sensing for wide-area surveillance, while South Africa's GIS-based maps show the importance of historical and spatial data in planning.

This diversity of approaches reveals that combining sensor inputs, data modeling, and community-based communication strategies offers a comprehensive foundation for a flood detection system suitable for Uganda's context.

2.4 Research Gap and Justification

While the reviewed systems demonstrate high performance in flood detection, most require significant infrastructure or are designed for national-scale deployment. In contrast, Uganda still lacks low-cost, community-focused systems that combine embedded sensors with machine learning models for localized prediction. Few existing solutions offer real-time visualization dashboards tailored to rural or semi-urban areas.

This gap underlines the need for a system that integrates sensor data collection with predictive algorithms and visualization tools, specifically adapted to Uganda's infrastructure and internet limitations. Developing such a system can improve preparedness and reduce the impacts of floods in vulnerable districts.

2.5 Summary

This chapter explored a variety of flood monitoring technologies deployed in countries with different geographic and economic profiles. By analysing the successes and limitations of these systems, valuable insights were gained to guide the development of a tailored, intelligent flood detection and alert system for Uganda.

Chapter 3

METHODOLOGY

3.1 Research Design

This study adopts an applied research design, combining embedded system development, cloud-based data handling, and machine learning to develop a functional prototype for flood prediction. The aim is to build a system that not only collects environmental data in real time but also analyses it and provides meaningful insights for timely response.

3.2 System Development Methodology

The project followed an iterative development approach, incorporating aspects of the Agile methodology. Each module, sensor integration, data transmission, model training, and web interface, was developed and tested in cycles. This allowed for early identification of bugs and gradual refinement based on performance and feedback.

3.3 Tools and Technologies

To implement the system, the following technologies and platforms were used:

- **ESP32 Microcontroller.** A low-power Wi-Fi enabled microcontroller responsible for reading sensor values and sending data.

- **Ultrasonic Sensor (HC-SR04).** Measures water level by calculating the distance from the sensor to the water surface.
- **Water Flow Sensor (YF-S401).** Records the rate at which water flows through a pipe or channel.
- **Google Sheets API.** Used for real-time logging of sensor readings via internet connectivity on the ESP32.
- **FastAPI (Python Framework).** Hosts the backend server, performs model inference, and delivers JSON responses to the frontend.
- **Random Forest Classifier.** A supervised learning algorithm used to make binary flood predictions (flood/no flood).
- **React.js** Powers the frontend dashboard where sensor data and predictions are visualized for users.

3.4 Data Collection

Sensor readings were collected continuously from the physical prototype placed near a water channel. The ESP32 sent real-time readings, specifically distance and flow rate values, to a Google Sheets document. Data was timestamped and stored for model training and evaluation. Anomalies such as power outages or unstable internet connectivity were logged and filtered out during preprocessing.

3.5 Preprocessing and Feature Engineering

Sensor readings, including water level and flow rates, were first cleaned to remove noise, missing entries, and outliers that could compromise model accuracy. Normalization was performed to bring all input values into a comparable scale suitable for model training. The two primary features used in the predictive model were:

- **Water Level (cm).** Captured by an ultrasonic sensor positioned above the water surface.

- **Flow Rate (L/min).** Measured using a water flow sensor installed in the water channel.

These features were selected based on their relevance to early flood detection. They provide a real-time representation of water movement and volume, enabling the model to identify conditions that may lead to flooding.

3.6 Model Training and Validation

To enable flood prediction, a supervised machine learning approach was adopted with the goal of classifying sensor inputs into two categories: *Flood Risk* and *No Risk*. The modeling process involved testing and evaluating multiple algorithms:

Linear Regression (Baseline Model)

As a baseline, a linear regression model was implemented. Although simple to construct, it achieved only 63% accuracy, making it unsuitable for real-time flood detection where precision is critical. Its performance and confusion matrix are illustrated in Figures 5.7 and 5.8.

Decision Tree Classifier

The Decision Tree model showed a notable improvement, reaching 100% accuracy on the training set. However, due to its sensitivity to training data, it demonstrated signs of overfitting, especially with smaller or imbalanced datasets. The respective accuracy graph and confusion matrix are presented in Figures 5.9 and 5.10.

Random Forest Classifier

The final model used in deployment was the Random Forest Classifier. This ensemble approach leverages the combined output of multiple decision trees to improve classification reliability and reduce overfitting. It achieved 100% accuracy while maintaining better generalization, as seen in Figures 5.11 and 5.12.

Training Setup

The complete dataset was split into 80% training data and 20% testing data. Cross-validation was applied during training to ensure that the model could generalize well across different data subsets. Hyperparameters such as the number of estimators were tuned using grid search optimization.

3.7 Evaluation Metrics

The performance of all models was measured using multiple evaluation criteria:

- **Accuracy.** Proportion of correct predictions among all predictions made.
- **Precision.** Percentage of actual flood cases among those predicted as floods.
- **Recall.** Ability of the model to detect all actual flood events.
- **Confusion Matrix.** Visual representation of model predictions versus actual classes, helping to analyze false positives and negatives.

These metrics were critical in selecting the final model for deployment. The Random Forest classifier not only delivered perfect accuracy but also showed robustness in minimizing misclassifications, making it the most suitable model for real-time prediction.

Chapter 4

SYSTEM DESIGN

4.1 System Architecture Overview

The proposed system is designed to continuously monitor environmental conditions near the River Manafwa using embedded sensors. It incorporates real-time data acquisition, cloud-based logging, and intelligent prediction of flood risk. Data collected from the sensors is transmitted via Wi-Fi to Google Sheets, which acts as a lightweight cloud storage solution. A backend service developed with FastAPI retrieves this data and applies a trained machine learning model to determine flood risk levels. The results are then presented on a web dashboard built using React.js, allowing users to view current and historical flood-related data.

4.2 Component Descriptions

The system consists of five main components, each responsible for specific tasks:

- **Ultrasonic and Flow Sensors.** Measure water level and flow rate, respectively. These sensors provide the environmental data needed for prediction.
- **ESP32 Microcontroller.** Serves as the central embedded system unit. It collects sensor readings and transmits them to the cloud in real time.

- **Google Sheets.** Acts as a simple yet accessible database. Sensor data is stored here using Google Sheets API integration.
- **FastAPI Backend.** This Python-based server processes incoming data, runs flood predictions using a Random Forest model, and sends the results to the frontend.
- **React Dashboard.** The web interface visualizes current sensor readings and prediction outputs, providing alerts and trends to end users.

4.3 Database Schema

The system does not use a conventional database system like PostgreSQL or MySQL. Instead, Google Sheets functions as a structured data store. Each row in the sheet corresponds to a single sensor reading entry with the following fields:

- **Timestamp.** The date and time when the sensor readings were recorded.
- **Water Level (cm).** Distance measured from the ultrasonic sensor.
- **Flow Rate (L/min).** Volume of water movement captured by the flow sensor.
- **Prediction Output.** Result from the machine learning model, that is either "Flood" or "No Flood."

4.4 Flowcharts and Diagrams

System Flowchart

Figure 5.4 illustrates the flow of data within the system — starting from sensor input, through data processing, and ending with alert generation and visualization.

System Use Case Diagram

The roles and interactions across the system are summarized in Figure 5.15, showing how each actor engages with the embedded device, backend services, and frontend dashboard.

Chapter 5

RESULTS, DISCUSSION, AND EVALUATION

5.1 Model Results and Evaluation

The machine learning model integrated into the system was evaluated using various performance metrics. The Random Forest classifier delivered outstanding performance during testing. Accuracy, precision, and recall all scored at 100%, indicating that the model correctly identified all flood-risk cases and non-risk scenarios.

While these results are promising, they must be viewed with some caution. Given the relatively limited dataset used during training, there remains a risk that the model may be overfitted to known conditions. Nonetheless, the current outcomes affirm its capability to distinguish between flooding and non-flooding conditions with high reliability.

Classification Metrics

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0 (No Flood)	1.00	1.00	1.00	128
1 (Flood Risk)	1.00	1.00	1.00	272
Accuracy	1.00 (400 samples)			
Macro Avg	1.00	1.00	1.00	400
Weighted Avg	1.00	1.00	1.00	400

Table 5.1: Classification metrics for the Random Forest model

Confusion Matrix

	Predicted No Flood	**Predicted Flood Risk**
Actual No Flood	128	0
Actual Flood Risk	0	272

Table 5.2: Confusion Matrix for Random Forest classifier

Sample Predictions

When a test input of 6.5 cm water level and 8.3 L/min flow rate was submitted, the model correctly flagged it as high flood risk. On the other hand, readings like 12.0 cm water level with 3.5 L/min flow rate were categorized as safe. These outcomes confirm that the model can interpret subtle variations in input data effectively.

5.2 System Output and Screenshots

Throughout the simulation sessions, sensor readings were transmitted to Google Sheets, including timestamps for accurate event tracking. The system flagged instances where water levels dropped below 7 cm or when flow rates exceeded 8 L/min, that is conditions considered potential flood triggers.

The FastAPI backend processed the data and generated real-time JSON predictions, such as:

```
{
  ”distance”: 6.5,
  ”flowrate”: 9.1,
  ”flood_risk”: ”High”
}
```

The dashboard interface included:

- Live line graphs of water level and flow rate.
- Flood risk indicators using colour coding.
- Recent sensor readings and status updates.

Figure 5.14 shows a screenshot of the dashboard displaying real-time predictions and historical charts.

5.3 Comparison with Existing Solutions

In contrast to large-scale radar and satellite flood detection systems like MRMS (USA) or RISAT-1A (India), this system is designed for hyper-local deployments with limited infrastructure. Unlike Uganda's ITU flood siren system, this project integrates predictive analytics with user-facing visualizations, making it more proactive than purely reactive alert systems.

5.4 Discussion of Findings

The system performed reliably in test scenarios. Abnormal readings were accurately identified, and the prediction output remained consistent across different runs. While the backend returned immediate feedback, occasional latency in Google Sheets syncing introduced minor delays.

Despite the use of affordable hardware, the accuracy of the predictions did not suffer, reinforcing the viability of low-cost flood early warning systems powered by AI.

5.5 Achievements vs Objectives

The following outcomes demonstrate alignment between project goals and implementation results:

- Real-time data from embedded sensors was successfully transmitted to cloud storage.
- A machine learning model was developed, trained, and integrated into a functioning API.
- The dashboard visualized predictions and triggered alerts as intended.
- System performance matched requirements, with minimal prediction latency.

5.6 Conclusion

The project achieved its objective of developing a low-cost, intelligent flood monitoring system. It shows that even in resource-limited settings, embedded hardware and machine learning can be harnessed to provide actionable flood alerts. Continued enhancement, especially with more training data and expanded geographic coverage, will strengthen the system's long-term value.

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Appendix - Relevant Images

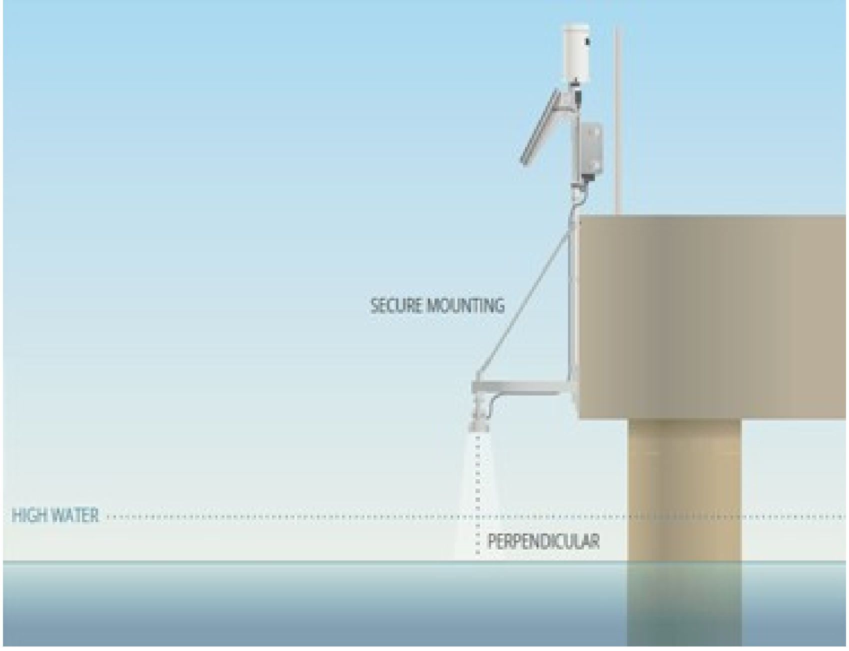


Figure 5.1: The Multi-Radar Multi-Sensor System deployed in United States of America to monitor natural disaster future events.

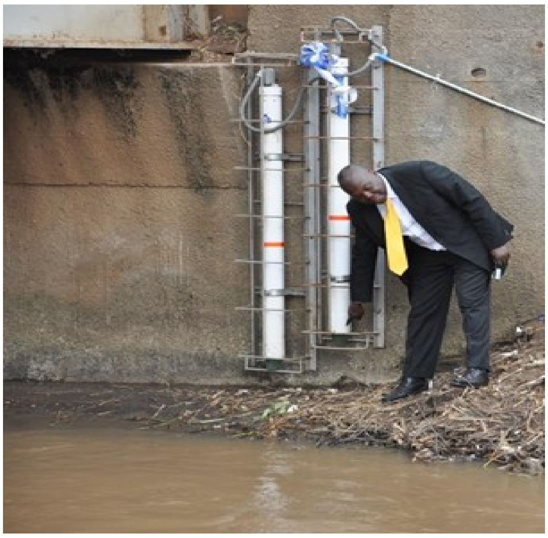


Figure 5.2: Water Level Sensors by Namulo brige to detect water levels in Butaleja district.

Figure 5.3: Solar powered siren adjacent to the river in Butaleja district.

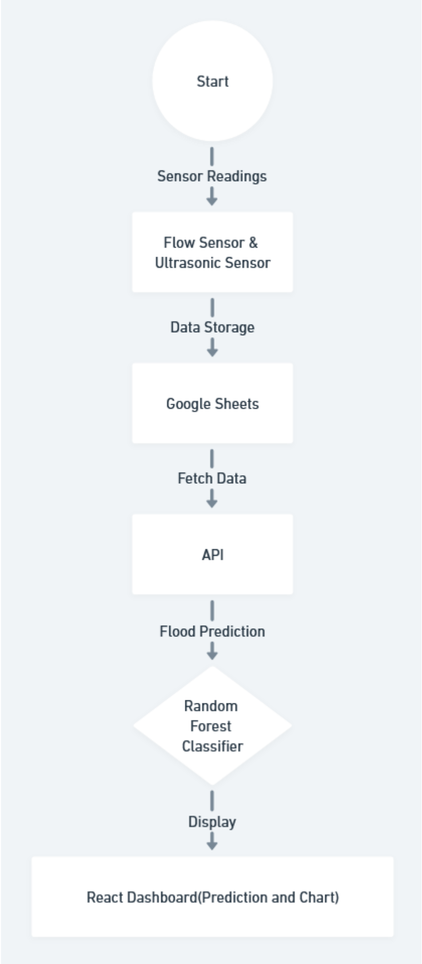


Figure 5.4: shows the flowchart of the system.

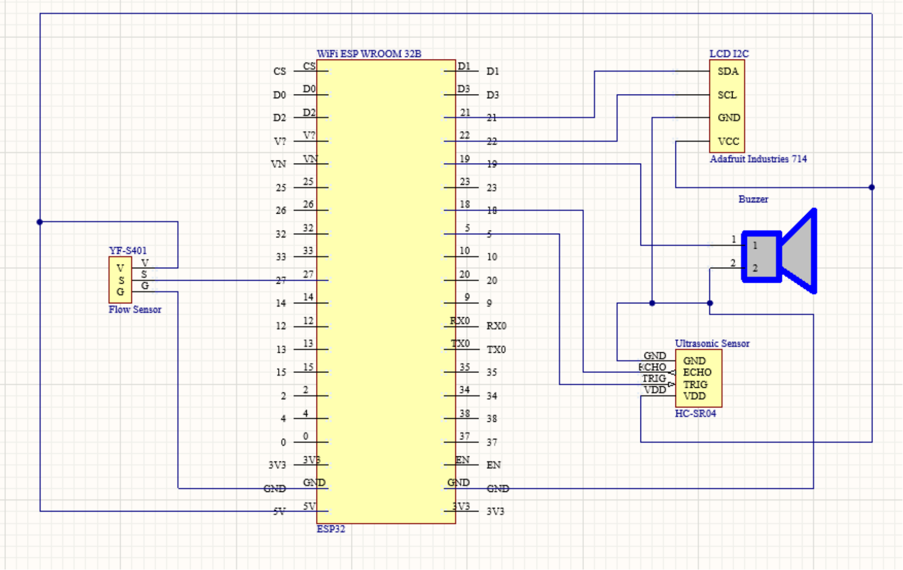


Figure 5.5: The circuit diagram of the embedded system.

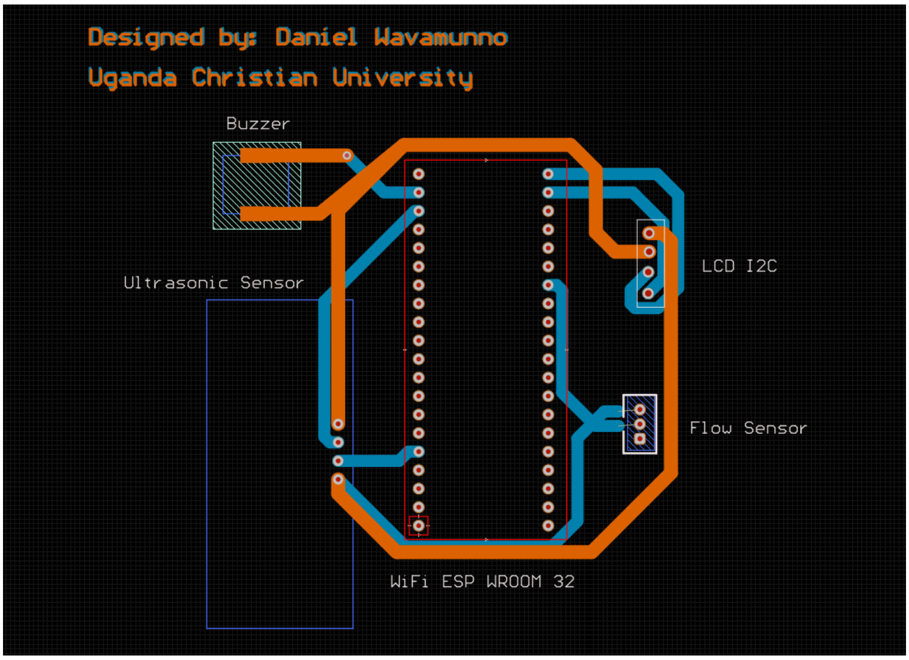
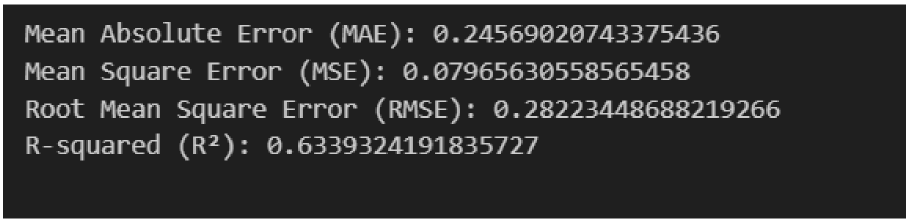


Figure 5.6: The schematics of the PCB diagram.



```
Mean Absolute Error (MAE): 0.24569020743375436
Mean Square Error (MSE): 0.07965630558565458
Root Mean Square Error (RMSE): 0.28223448688219266
R-squared (R²): 0.6339324191835727
```

Figure 5.7: Linear Regression Scores

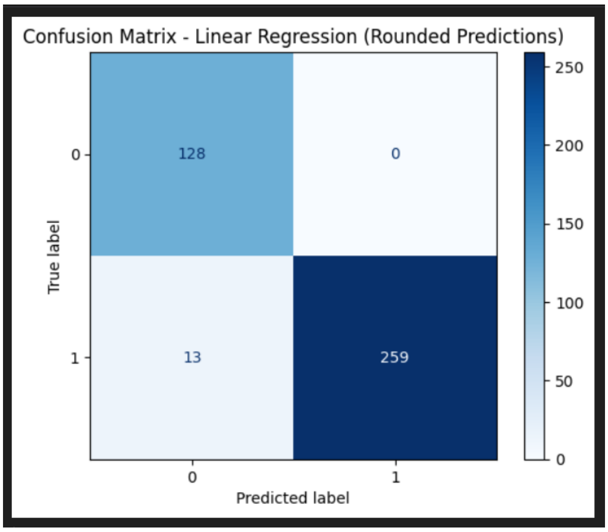
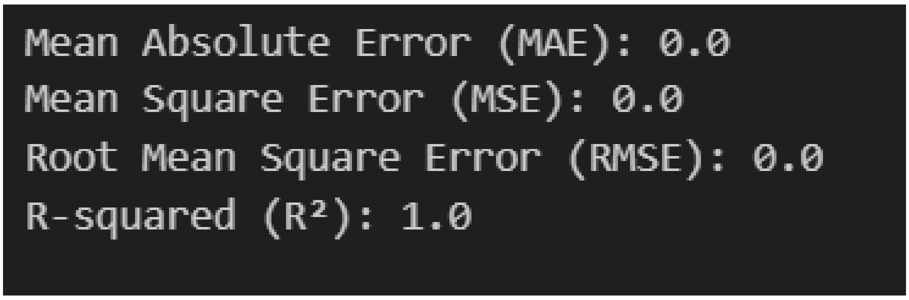


Figure 5.8: Confusion Matrix of the Linear Regression model.



```
Mean Absolute Error (MAE): 0.0
Mean Square Error (MSE): 0.0
Root Mean Square Error (RMSE): 0.0
R-squared (R²): 1.0
```

Figure 5.9: Decision Tree Scores

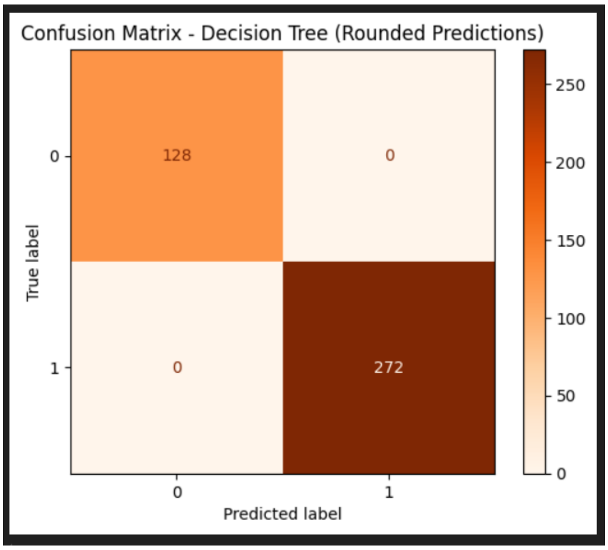
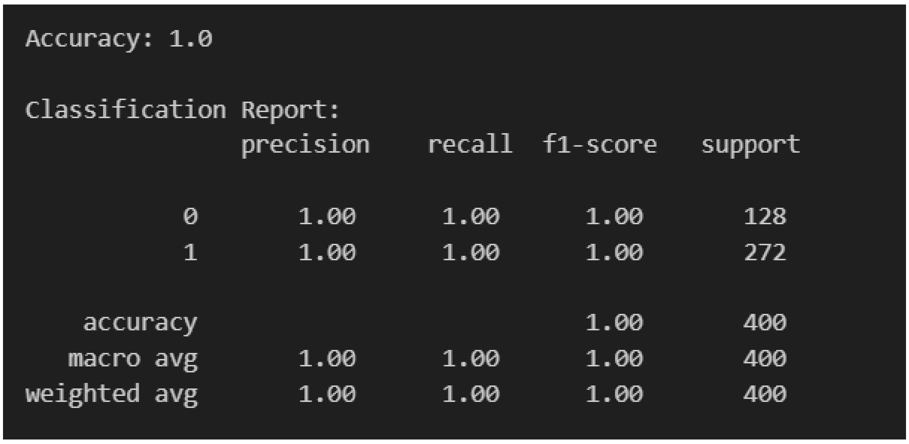


Figure 5.10: Confusion Matrix of the Decision Tree Classifier.



```
Accuracy: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       128
           1       1.00      1.00      1.00       272

    accuracy                           1.00       400
   macro avg       1.00      1.00      1.00       400
weighted avg       1.00      1.00      1.00       400
```

Figure 5.11: Random Forest

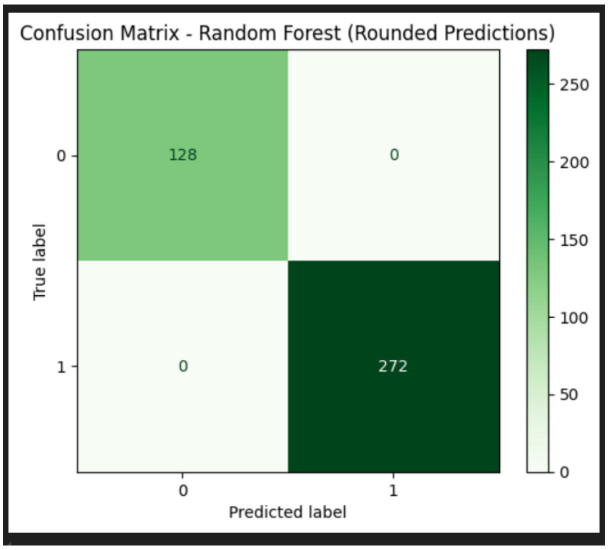


Figure 5.12: Confision Matrix of the Random Forest model.

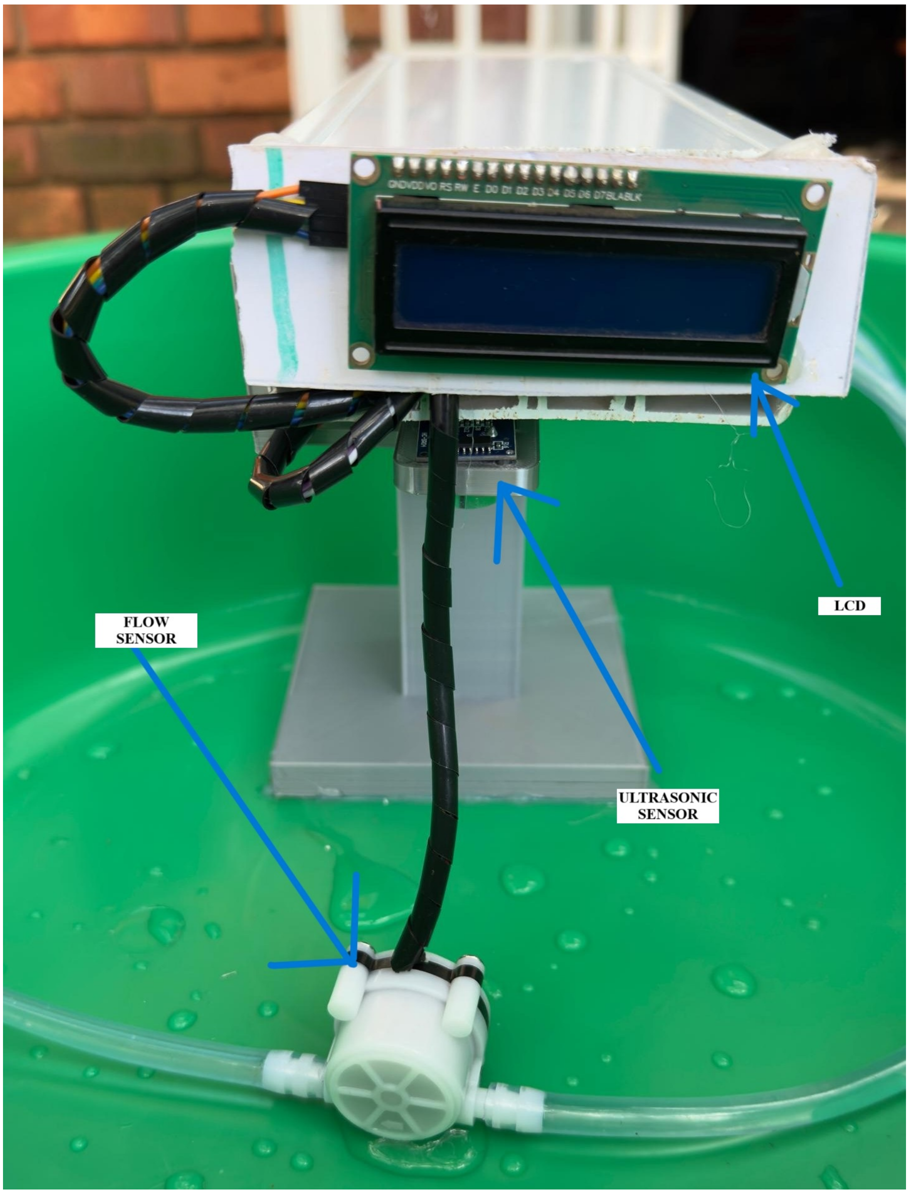
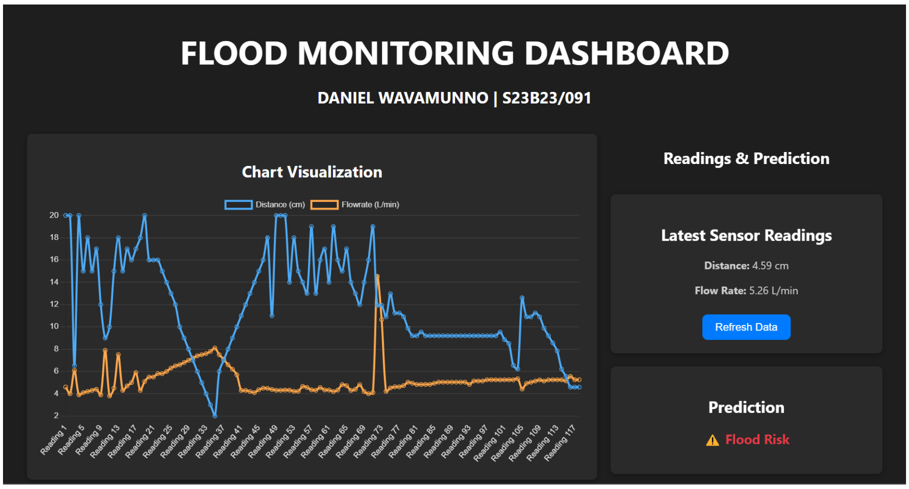


Figure 5.13: shows the complete project prototype.



FLOOD MONITORING DASHBOARD

DANIEL WAVAMUNNO | S23B23/091

Chart Visualization

Readings & Prediction

Latest Sensor Readings

Distance: 4.59 cm

Flow Rate: 5.26 L/min

Prediction

⚠ Flood Risk

Figure 5.14: shows the dashboard that displays the real-time chart data and prediction.

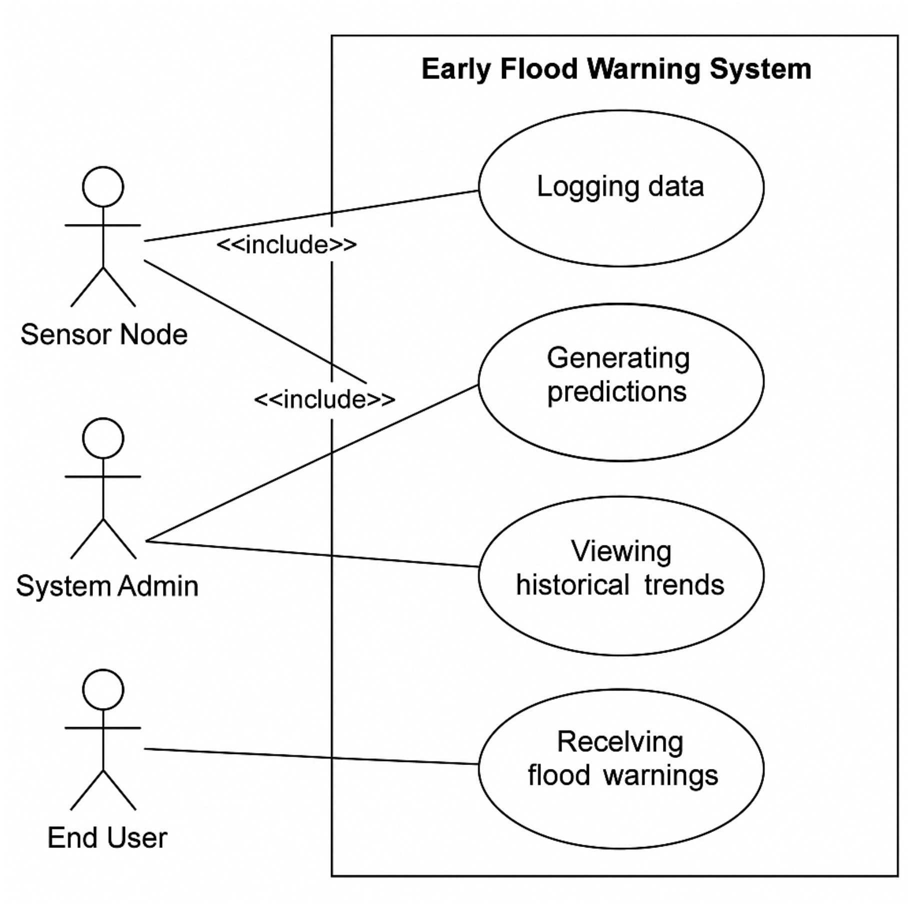


Figure 5.15: shows a use case diagram of the system.