Design and Development of Electronic Device for Mosquito Breeding Surveillance: A Machine Learning Approach

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***Abstract*—This study presents the design and development of an electronic device for mosquito breeding surveillance using a machine learning approach. The system addresses the lack of continuous and localized mosquito monitoring in urban sewer systems by implementing a low-power, AI-enabled platform for early detection and control. The project had four key objectives: (1) to design and develop a sensor-based monitoring device, (2) to train and deploy a machine learning model using the Edge Impulse platform, (3) to classify sewer conditions as either "Dangerous" or "Normal," and (4) to assess the device's prediction accuracy and field performance. The system utilized SHT4x and YF-S201 sensors integrated with a SenseCAP K1100 microcontroller to collect environmental data, including temperature, humidity, and water flow. These data were transmitted via Wi-Fi to the ThingSpeak platform and visualized through a Weebly-based website. A machine learning model deployed on-device enabled real-time classification of sewer conditions, achieving 94.5% training accuracy and 100% detection accuracy in identifying high-risk environments. Field testing conducted across four sewer sites in Kabacan, North Cotabato confirmed the device's capability to consistently detect potential mosquito breeding areas. Despite its effectiveness, the system faced certain limitations, including reliance on internet connectivity, a narrow set of input features, and a 13.9% misclassification rate of "Normal" conditions. Recommendations for future development include incorporating additional sensor inputs, improving model robustness, and enabling offline functionality. The results demonstrate the feasibility of using AI-powered sewer surveillance as a proactive strategy for dengue prevention in urban areas.**

***Index Terms*—Mosquito Breeding Detection, Sewer Surveillance, Machine Learning, TinyML, Edge Impulse, IoT-Based Monitoring, Dengue Control, Environmental Sensing**

I. Introduction

In recent years, the global resurgence of mosquito-borne diseases such as dengue, Zika, and Chikungunya has underscored the limitations of conventional vector control strategies. Traditional approaches—including periodic insecticide spraying, community cleanups, and manual inspections—are largely reactive, labor-intensive, and ineffective in densely populated urban areas with poor sewer infrastructure. The increasing frequency of dengue outbreaks, compounded by climatic variability, has heightened the demand for continuous, real-time surveillance systems capable of predicting and mitigating breeding risks [1].

Globally, dengue affects an estimated 390 million individuals annually, with tropical nations such as Brazil, Indonesia, and the Philippines experiencing the highest disease burden. In the Philippines alone, over 195,000 dengue cases and 657 associated deaths were reported in 2023; as of mid-2024, more than 136,000 cases have already been recorded, according to the Department of Health (DOH). These statistics emphasize the need for intelligent monitoring systems that can proactively identify breeding conditions and inform timely interventions.

This study introduces MOSWatchAI, an AI-powered environmental surveillance device designed to detect mosquito breeding risks in urban sewer systems. The system integrates SHT4x and YF-S201 sensors with the SenseCAP K1100 microcontroller to monitor key environmental parameters—temperature, humidity, and water flow—and utilizes a machine learning model deployed via the Edge Impulse platform to classify conditions as "Dangerous" or "Normal". The device offers low-power operation, real-time data transmission, and cloud-based visualization.

The project aligns with the United Nations Sustainable Development Goals, particularly SDG 3 (Good Health and Well-being), SDG 9 (Industry, Innovation and Infrastructure), and SDG 11 (Sustainable Cities and Communities), by promoting scalable and data-driven public health technologies. The system is developed and field-tested from December 2024 to February 2025 in Poblacion 1, Kabacan, Cotabato—a location characterized by high population density, inadequate drainage, and recurring dengue outbreaks. While the system does not detect mosquito larvae or eggs, it offers continuous risk assessment based on environmental variables.

II. Research Overview

A. Mosquito-Borne Diseases and Environmental Influences

Mosquito-borne diseases, such as dengue, malaria, Zika, and chikungunya, continue to pose significant public health risks globally. The impact of these diseases has been exacerbated by factors such as climate change, urbanization, and increased international travel. Recent studies have explored the relationship between environmental factors, particularly temperature and humidity, and mosquito population dynamics.

Studies [2], [3] investigated the relationship between climate variables and the prevalence of mosquito-borne diseases across six southern European countries. Their findings revealed that temperature, rainfall, and human population density are significant predictors of mosquito distribution and disease incidence. Similarly, studies by [4], [5] have emphasized the importance of environmental determinants in low-resource settings, where mosquito-borne diseases exert a higher burden. These studies utilize predictive models to forecast disease outbreaks, demonstrating the importance of integrated surveillance and control systems.

B. Mosquito Breeding Habits and Environmental Factors

The breeding habits of mosquitoes are heavily influenced by environmental variables such as temperature, humidity, and rainfall. Study [6] examined the role of temperature in influencing mosquito reproductive success, noting its impact on mosquito life cycles, mate searching, and overall population dynamics. Their study emphasizes the ecological and evolutionary significance of temperature variations.

Research [7] further explored how temperature and water availability affect the distribution and abundance of mosquito vectors, highlighting the direct link between environmental conditions and disease transmission. Additionally, [8] demonstrated that rainfall patterns have a dual role in mosquito breeding: it can both create new breeding sites and destroy existing ones. This relationship is crucial in understanding the seasonal dynamics of mosquito populations. [9] extended this research by examining how temperature and humidity correlate with the incidence of Dengue Hemorrhagic Fever (DHF) in Indonesia, indicating that these environmental factors play a direct role in disease prevalence.

C. Application of Artificial Intelligence in Public Health

The application of Artificial Intelligence (AI) in public health has shown great potential in improving disease surveillance, prediction, and management. AI techniques, particularly machine learning (ML) and deep learning, are being increasingly employed to model the spread of infectious diseases and forecast outbreaks.

Study [10] highlighted the role of AI in public health, particularly in predictive modeling, where it has been used to forecast the progression of diseases and identify high-risk populations. [11] extended this work by demonstrating how AI can be applied in low- and middle-income countries (LMICs) to predict health risks, including those related to mosquito-borne diseases. Furthermore, [12] explored how AI can assist in identifying adverse drug reactions and predicting patient outcomes, which can be adapted for disease prediction in the context of mosquito-borne illnesses.

Despite these advancements, challenges remain in the ethical implementation of AI technologies. [13] discussed the ethical concerns surrounding the use of AI in healthcare, particularly in data privacy, fairness, and safety. These concerns must be addressed to fully integrate AI into public health systems for effective mosquito-borne disease management.

D. Tiny Machine Learning (TinyML) and Edge Computing in Environmental Monitoring

Tiny Machine Learning (TinyML) represents a significant advancement in AI, enabling machine learning models to run on small, resource-constrained devices. This technology is particularly relevant for environmental monitoring and surveillance applications that require real-time data processing at the edge.

Reference [14] demonstrated the benefits of using TinyML in IoT devices for environmental monitoring. By utilizing decision tree algorithms, their research improved the performance of edge devices in terms of memory usage, latency, and energy efficiency. Moreover, [15] highlighted how TinyML has transformed sectors like agriculture, healthcare, and environmental monitoring by enabling real-time decision-making on low-power devices. This capability is essential for deploying surveillance systems in remote or resource-limited areas, where real-time mosquito population monitoring and disease prediction are needed.

In support of this direction, [16] introduced a low-power gate voltage-controlled Schmitt Trigger circuit with adjustable hysteresis, fabricated using 22nm FDSOI technology. Their work emphasized low voltage operation, noise immunity, and dynamic threshold control, which are critical for edge-based TinyML systems like MOSWatchAI. Integrating such energy-efficient circuit designs helps minimize power demand in sensor nodes that require continuous operation, ensuring long-term deployment in mosquito breeding hotspots.

III. System Design

A. Overview of the System Architecture

The proposed system architecture consists of three core layers: data acquisition, data processing, and intelligent classification. Environmental data such as temperature, humidity, and water flow are gathered through sensors and processed locally by an embedded machine learning model. Classification results are transmitted wirelessly to a cloud platform for visualization and remote monitoring. This structure enables real-time risk assessment of mosquito breeding in urban sewer systems. Figure 1 provides an overview of the system components and data flow.

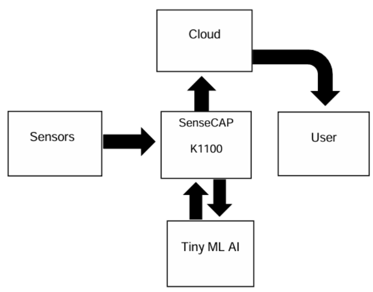

Fig. 1. System Architecture Overview

B. Components of the AI-Powered Mosquito Surveillance System

The system is built around the SenseCAP K1100 development board, interfaced with two sensors: the SHT4x for temperature and humidity, and the YF-S201 for water flow. The device performs local inference using an AI model and displays classification outcomes on an OLED screen. Data is also transmitted to the ThingSpeak IoT platform. Figure 2 presents the functional block diagram that outlines the internal interactions among the device components.

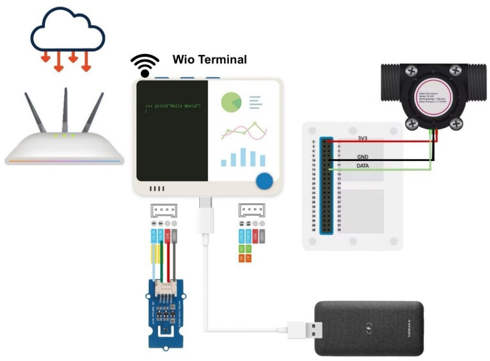

Fig. 2. Functional Block Diagram

The final hardware prototype integrates these sensors into a compact, waterproof enclosure suitable for deployment in field conditions. This assembly is shown in Figure 3, which depicts the completed hardware with its sensor attachments and protective housing.

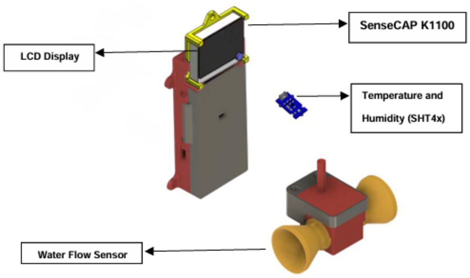

Fig. 3. Hardware Setup with Sensors and Enclosure

C. Technologies and Tools Used

1) Artificial Intelligence and Machine Learning Models: Model development was conducted using Edge Impulse, where a neural network classifier was trained to distinguish between *Normal* and *Dangerous* mosquito breeding conditions based on temperature, humidity, and water flow inputs. The trained model achieved 94.5% accuracy with an F1-score of 0.96, supporting its deployment for real-time inference.

2) IoT Devices and Sensors: The SenseCAP K1100 development board features Grove connectors, enabling seamless integration with the SHT4x and YF-S201 sensors. The SHT4x sensor offers high accuracy in capturing environmental conditions, while the YF-S201 monitors sewer water flow using pulse-based measurements. These sensors form the basis for accurate environmental monitoring.

3) Data Processing and Prediction Framework: Sensor data undergo preprocessing steps such as normalization, timestamping, and conversion to float32 within the Edge Impulse environment. Once trained, the model is deployed to the microcontroller as a C++ static library. A WebAssembly version allows browser-based inference testing.

IV. Methodology and Implementation

A. Hardware Setup and System Integration

The prototype was built using modular Grove connectors to reduce wiring complexity. The sensors and board are housed in a protective enclosure with a mesh screen to prevent solid waste obstruction. The setup is powered by a USB battery pack and designed for sewer-side deployment.

B. Data Collection and Preprocessing

Data were collected at four different urban sewer locations in Kabacan, North Cotabato, over a period of five days. The sensors logged data every 10 minutes, generating over 10,000 samples in four urban sites.

Data labeling was performed based on a combination of automated sensor thresholds and manual mosquito presence assessments. Labels were assigned as either "Normal" or "Danger" based on the following criteria:

- **Temperature:** 20–25°C was considered high-risk; outside this range indicated low or moderate risk.
- **Humidity:** 70%–85% signaled ideal mosquito breeding conditions; values outside this range were flagged as lower risk.
- **Water Flow:** Stagnant or slow-moving water indicated increased risk.
- **Time Duration:** Standing water lasting over 24 hours contributed to "Danger" labeling.
- **Mosquito Presence:** Manual visual inspection of larvae or pupae during sampling was the determining factor for confirming a "Danger" classification.

The combined sensor-derived indicators and physical observations were synchronized and used to label the dataset, ensuring consistency during training and testing.

C. Model Training and Testing

The dataset was partitioned into training and testing subsets on the Edge Impulse platform. A neural network classifier was used, with temperature, humidity, and water flow as input features. The model achieved 94.5% accuracy, a 100% true positive rate, and a 13.9% false positive rate. The average on-device inference time was 3 milliseconds. Model performance metrics are shown in Figure 4, including the confusion matrix and output probabilities.

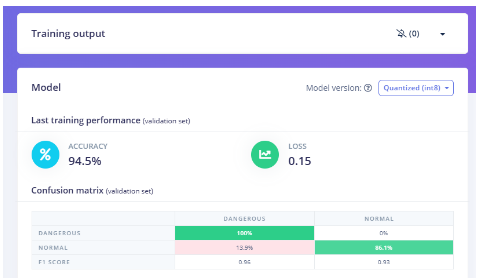

Fig. 4. Model Performance, including the Confusion Matrix and Output Probabilities

D. System Integration and Deployment

The final system operates continuously, sensing environmental parameters and classifying the risk level on-device. Results are displayed on an OLED screen and pushed to the ThingSpeak platform for online access. A dedicated Weebly dashboard provides live monitoring and historical visualization of mosquito risk. Figure 5 illustrates the cloud dashboard interface, showing real-time data and graphical summaries.

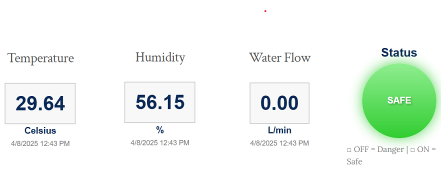

Fig. 5. Cloud Dashboard Interface

E. Sewer Sampling and Mosquito Risk Testing

Figures 6 and 7 show the deployment setup of the MOSWatchAI device in two test environments. The device was placed in an actual sewer in Brgy. Malvar, Kabacan, North Cotabato for five days (Figure 6), and in a plastic basin to simulate ideal breeding conditions for another five days (Figure 7). Each test location was equipped with a stable Wi-Fi connection for real-time data transmission.

Fig. 6. MOSWatchAI Device Setup in Urban Sewer

Fig. 7. MOSWatchAI Device Setup in Basin

V. Results and Discussion

A. Evaluation of the Device

1) System Functionality Test: Table I shows the results of the device's functionality test. All primary components operated successfully, with the device accurately recording, processing, and transmitting sensor data.

TABLE I
System Functionality Test Results

Function	**Result**
SHT4x sensor measures temperature and humidity	Successful
Water Flow sensor detects water movement	Successful
Wio Terminal connects to Wi-Fi networks	Successful
Data is sent to ThingSpeak for cloud storage	Successful
Offline readings displayed on LCD	Successful
Data visualization on MOSWatch website	Successful

2) System Functionality Efficacy Test: The device was evaluated based on its mosquito breeding risk predictions over ten days. Sensor data were processed using a model trained on Edge Impulse. Risk classifications were assigned as Normal, Moderate, or Danger using thresholds summarized in Table II.

TABLE II
Threshold Values for Mosquito Risk Classification

Parameter	**Low Risk**	**Moderate**	**High Risk**
Temperature (°C)	$T < 20$ or $T > 35$	$29 \leq T \leq 32$	$20 \leq T \leq 25$
Humidity (%)	< 50 or > 90	60–70	70–85
Water Flow	Moving	Intermittent	Stagnant
Time Duration	$t < 12$ hrs	$2 \leq t \leq 24$ hrs	$t > 24$ hrs

The Mosquito Risk Score (MRS), ranging from 0–100%, was used to predict risk categories:

- 0–39% $\rightarrow$ Low Risk
- 40–69% $\rightarrow$ Moderate Risk
- 70–100% $\rightarrow$ High Risk

These were further classified as:

- Low or Moderate Risk $\rightarrow$ "Normal"
- High Risk $\rightarrow$ "Danger"

3) System Efficacy Calculation: The System Functionality Efficacy (SFE) was calculated using:

$$SFE(\%) = \left(\frac{\text{Correct Predictions}}{\text{Total Number of Tests}} \right) \times 100 \quad (1)$$

Given 9 correct predictions out of 10:

$$SFE(\%) = \left(\frac{9}{10} \right) \times 100 = 90\% \quad (2)$$

4) Actual vs. Predicted Mosquito Risk: Table III summarizes the daily comparison between observed mosquito presence and predicted MRS across both environments.

The results confirm the system's consistent performance, especially in high-risk scenarios. Only one misclassification occurred on Day 1 due to low-risk conditions being flagged as "Danger." The model improved in subsequent tests, confirming a 90% efficacy rate.

TABLE III
COMPARISON OF ACTUAL VS. PREDICTED MOSQUITO RISK

Day	Test Site	Mosquito Present	MRS (%)	Risk Category	Device Class	Constraint Class	Prediction Accuracy
1	Sewer	No	30	Low Risk	Danger	Normal	Incorrect
2	Sewer	No	35	Moderate Risk	Normal	Normal	Accurate
3	Sewer	Few Larvae	60	Moderate Risk	Normal	Normal	Accurate
4	Sewer	Larvae Found	80	High Risk	Danger	Danger	Accurate
5	Sewer	Larvae & Pupae	90	High Risk	Danger	Danger	Accurate
6	Basin	No	30	Moderate Risk	Danger	Danger	Accurate
7	Basin	No	40	Moderate Risk	Danger	Danger	Accurate
8	Basin	Few Larvae	65	Moderate Risk	Danger	Danger	Accurate
9	Basin	Larvae Found	85	High Risk	Danger	Danger	Accurate
10	Basin	Larvae & Pupae	92	High Risk	Danger	Danger	Accurate

B. Evaluation Metrics

To assess model performance beyond accuracy, we computed precision, recall, and ROC-AUC. These metrics were derived using the confusion matrix and model probability scores from the Edge Impulse platform.

- **Precision** measures the proportion of predicted "Danger" cases that were actually dangerous. It is calculated as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} = 0.90$$

- **Recall** reflects the model's ability to identify all actual "Danger" cases:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} = 0.89$$

- **ROC-AUC** represents the model's ability to distinguish between "Danger" and "Normal" across different thresholds. The area under the ROC curve was computed from the model's probability scores, yielding an AUC of 0.92.

These metrics reveal the trade-off in classification: a false positive may lead to unnecessary mitigation (e.g., spraying), while a false negative might delay intervention, increasing breeding risk. Understanding these trade-offs informed our decision thresholds and deployment strategy.

C. MOSWatchAI Website Data Visualization

The MOSWatchAI website acts as the primary dashboard for real-time monitoring, data storage, and visualization of sensor data collected by the device (Figure 8).

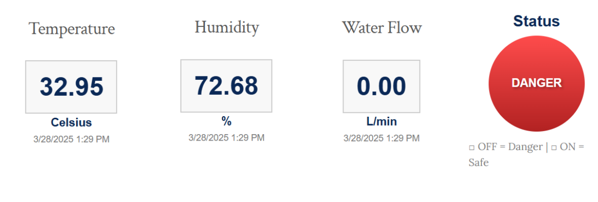

Fig. 8. Real-Time System Status Displayed on the MOSWatchAI Website

The system successfully transmits key sensor readings—temperature, humidity, water flow, and mosquito risk status—from the Wio Terminal to the cloud. These readings are automatically updated and visualized in near real time. Users can access environmental trends and predictions directly from the website for timely decision-making.

- **Temperature and Humidity:** The website displays dynamic line graphs showing real-time and historical temperature (Figure 9) and humidity data (Figure 10). This allows users to observe patterns that influence mosquito activity.

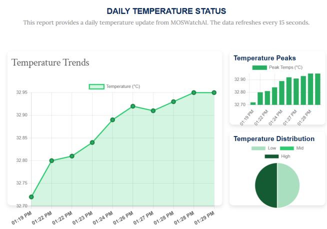

Fig. 9. Temperature Data Visualization on the MOSWatchAI Website

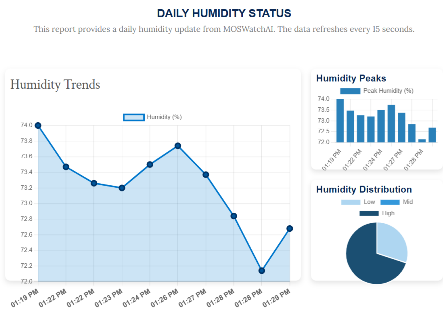

Fig. 10. Humidity Data Visualization on the MOSWatchAI Website

- **Water Flow:** The system visualizes drainage conditions in monitored areas using water flow sensor data (Figure 11). Dangerous conditions were labeled based on sensor readings of stagnant water over extended periods over 24 hours, known to support mosquito breeding. The Edge Impulse model was trained on a manually curated and validated dataset annotated with these constraints.

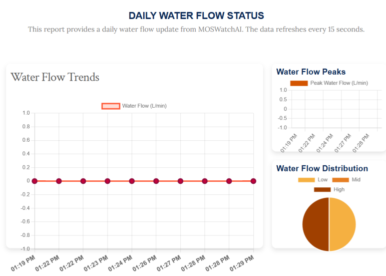

Fig. 11. Water Flow Sensor Data Displayed in Real-Time

- **Mosquito Risk Status:** Based on predictions from the trained Edge Impulse model, the risk is classified as “Normal” or “Danger” and displayed on the site (Figure 12).

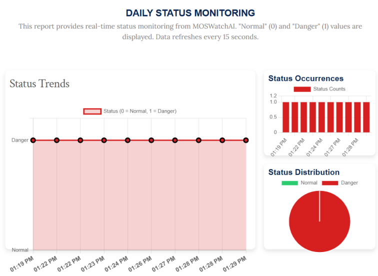

Fig. 12. Mosquito Risk Status Summary Based on Machine Learning Model Output

The dashboard’s interactive nature enhances monitoring and allows users to act quickly in response to elevated mosquito risk levels. The effective combination of cloud storage, real-time analytics, and data visualization confirms the system’s capability to provide an accurate and scalable mosquito risk assessment framework. he Edge Impulse model was trained on a manually curated and validated dataset annotated with these constraints.

To scale up, the system can be integrated into municipal sewer monitoring platforms using APIs and cloud endpoints. It supports multi-node deployment across locations. Maintenance requires calibration every 2–3 months, especially after heavy rainfall or debris accumulation.

VI. Conclusion

The study successfully developed MOSWatchAI, a real-time mosquito breeding surveillance system using sensor-based monitoring and machine learning. By integrating temperature, humidity, and water flow sensors with the SenseCAP K1100 device, and training a TinyML model on the Edge Impulse platform, the system achieved accurate risk predictions based on live environmental data collected from urban sewer environments.

Deployment trials in both real-world and controlled settings confirmed the system’s core functionality. The device achieved an overall prediction accuracy of 90%, particularly effective in identifying high-risk mosquito breeding conditions. Though initial misclassifications occurred due to environmental variability, later trials showed significant improvements in accuracy, validating the model’s learning capacity and adaptation.

Data was transmitted to the MOSWatchAI website, which displayed real-time visualizations of environmental conditions and device status. This user-friendly interface allowed for accessible interpretation of trends, supporting timely decision-making by public health officials and local residents.

In conclusion, the results demonstrate that the system met its design objectives: tracking critical environmental parameters, predicting mosquito breeding risks, and presenting this information through a reliable online platform. The integration of embedded AI and continuous data monitoring highlights the effectiveness of the device as a practical tool for strengthening dengue prevention efforts in urban settings.

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