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SIMULATION AND EVALUATION OF AN IOT-BASED INTELLIGENT AQUARIUM MONITORING AND CONTROL SYSTEM USING RANDOM FOREST CLASSIFICATION

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ABSTRACT

Maintaining stable aquarium water quality requires continuous monitoring and timely responses to environmental changes. This study presents a simulation-based evaluation of an Internet of Things (IoT)-enabled intelligent aquarium monitoring and control framework using Random Forest classification. Five input variables—water temperature, pH, turbidity, dissolved oxygen, and water level—were used to classify water quality into Safe, Warning, and Dangerous states. The Random Forest model employed 100 decision trees and was evaluated on a simulated test set of 150 samples using accuracy, precision, recall, F1-score, a confusion matrix, and feature importance. The model achieved 97.3% overall accuracy. Class-specific F1-scores were 0.991 for Safe, 0.965 for Warning, and 0.961 for Dangerous. The highest model-derived feature importance scores were obtained for pH (0.248), water level (0.239), and temperature (0.218). These results indicate the preliminary feasibility of Random Forest-based decision support within a simulated aquarium monitoring framework. Because the dataset and control system were simulated, validation using real sensors and experimental aquarium conditions is required before practical deployment.

Keywords: Internet Of Things (Iot), Aquarium Monitoring, Water Quality, Random Forest, Machine Learning, Automated Control.

I. INTRODUCTION

Maintaining stable water quality is essential in household aquariums, ornamental fish systems, and laboratory aquatic environments because fish health is influenced by temperature, pH, dissolved oxygen, turbidity, water level, and other environmental conditions. IoT-based monitoring has therefore been increasingly applied to aquaponics and aquarium management. Dang et al. [2] developed an IoT system for remote environmental monitoring in a small-scale household aquaponics model, while Nguyen et al. [3] reported a mobile-enabled aquaponics monitoring and control system. Amrita et al. [4] proposed an IoT-based aquarium water-quality management system, and Aria et al. [5] integrated an ESP32 platform with pH, total dissolved solids, temperature, and turbidity sensing together with feeding and water-control actuators.

Continuous water-quality monitoring can support timely responses to unfavorable conditions. Parameters such as pH, temperature, dissolved oxygen, turbidity, and total dissolved solids are commonly considered in aquaculture monitoring [6–8]. However, conventional manual sampling and laboratory analysis can be labor-intensive, costly, and unsuitable for immediate detection of rapid parameter changes [9–11]. Recent aquaculture research has consequently explored machine-learning and deep-learning methods for feeding, disease detection, behavior analysis, and water-quality assessment [12,14,16].

This study evaluates a simulation-based IoT aquarium monitoring and control framework using a Random Forest classifier. The model classifies simulated aquarium conditions into Safe, Warning, and Dangerous states from five input variables: water temperature, pH, turbidity, dissolved oxygen, and water level. The study focuses on classification performance, confusion-matrix behavior, and model-derived feature importance, while the proposed hardware architecture is presented as a basis for future real-sensor implementation and experimental validation.

II. LITERATURE REVIEW

Previous studies have demonstrated the value of IoT platforms for continuous aquaculture monitoring. Al Mamun et al. [15] developed a real-time biofloc monitoring and control system using temperature, total dissolved solids, pH, turbidity, dissolved oxygen, and water-level sensing. Ahmed et al. [14] combined real-time IoT monitoring with predictive machine-learning analysis for aquaculture water-quality management. Together with other aquarium and aquaponics studies [2–5], this literature shows the potential of integrating sensing, communication, data processing, and decision support.

Within the literature reviewed for this study, three limitations remain relevant to small-scale intelligent aquarium monitoring: many systems emphasize threshold-based monitoring or hardware operation; machine-learning integration is less common in basic aquarium applications; and model evaluation is not always accompanied by detailed class-level performance and feature-importance analysis. The present study addresses these points through a simulation-based Random Forest evaluation across three water-quality states and reports accuracy, precision, recall, F1-score, a confusion matrix, and feature importance. The results are intended as a preliminary computational assessment rather than as experimental validation.

III. MATERIALS AND METHODS

3.1. Proposed System Architecture

The proposed system consists of four functional layers, as summarized in Figure 1.

Sensing Layer		IoT Processing Layer		Machine-Learning Layer		Control & Monitoring Layer
Temperature		WeMos D1 / ESP8266		Random Forest		Alert / notification
pH	→	Wi-Fi transmission	→	Safe / Warning / Dangerous	→	Pump / aeration / feeder
Turbidity		Database / logging		Feature importance		Dashboard
Dissolved oxygen						
Water level						

Figure 1. Conceptual four-layer architecture of the proposed IoT-based intelligent aquarium monitoring and control framework.

The sensing layer provides the five input variables used in the classification model: water temperature, pH, turbidity, dissolved oxygen, and water level. The IoT processing layer is represented by a WeMos D1/ESP8266-class microcontroller with Wi-Fi communication for receiving sensor readings, basic preprocessing, transmission, and data logging. The machine-learning layer applies the Random Forest model to classify the current condition as Safe, Warning, or Dangerous. The control and monitoring layer represents the proposed response stage, in which classification outputs can be linked to alerts, dashboards, and actuators such as aeration, pumping, or feeding devices. These hardware and control functions are conceptual in the present simulation-based study.

The proposed hardware interaction is shown in Figure 2. A WeMos D1 development board based on the ESP8266 is proposed as the central processing unit and provides integrated Wi-Fi connectivity. The board interfaces with the sensor block, power supply, data-storage service, and proposed actuator/display block.

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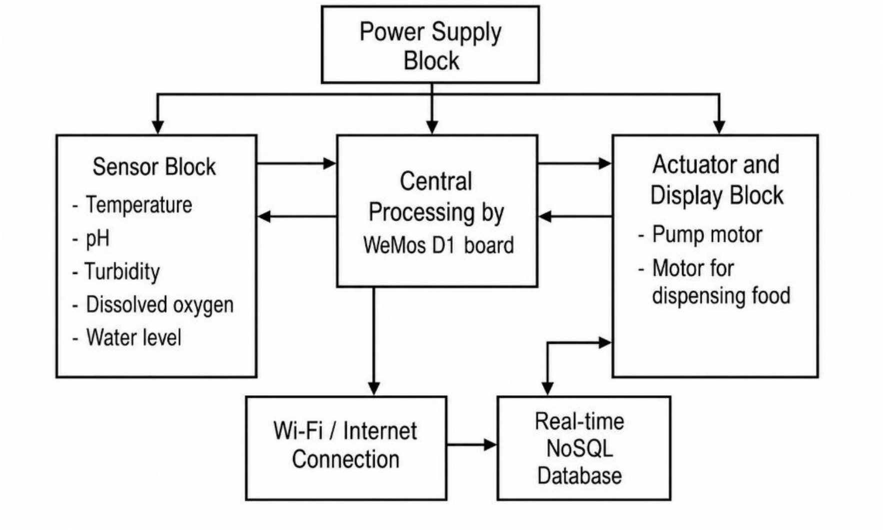

Figure 2. Proposed hardware block diagram of the IoT-based aquarium monitoring system.

Figure 3 summarizes the proposed five-step workflow. First, sensors collect aquarium water-quality data. Second, the measurements are transmitted to the ESP8266/ESP32-based processing unit. Third, the data are stored for analysis and logging. Fourth, the Random Forest model classifies the water-quality state. Fifth, the predicted state is used to generate a warning or a proposed control response.

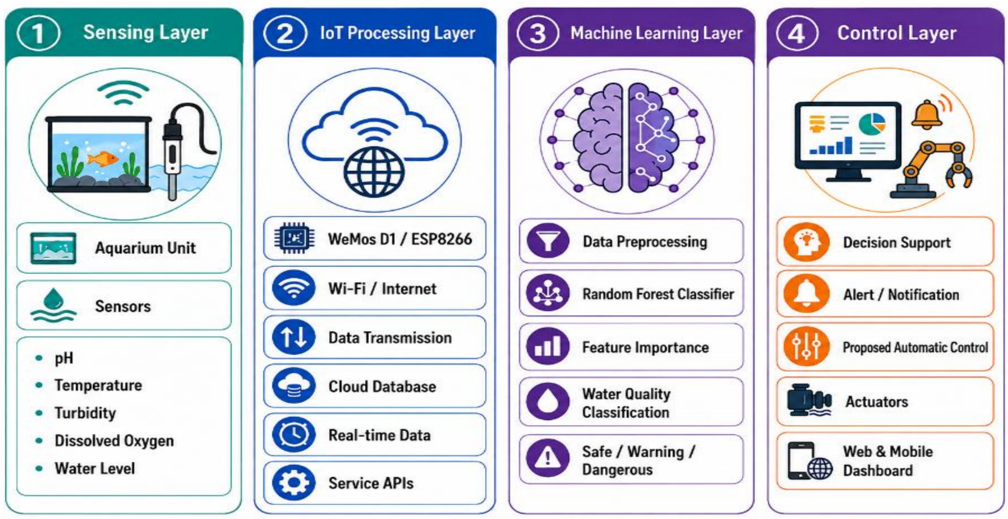

Figure 3. Workflow of the Random Forest-based aquarium water-quality classification process.

3.2. Random Forest Classification and Evaluation

The Random Forest classifier predicts the water-quality status from an input feature vector X_i:

$$X_i = [T_i, pH_i, Turb_i, DO_i, WL_i] \quad 1$$

where:

T_i: Water temperature (°C);

pH_i: Water pH value;

$Turb_i$: Turbidity (NTU);

DO_i: Dissolved oxygen (mg/L);

WL_i: Water level binary state (1: Normal, 0: Low);

The predicted output label Y_i belongs to the set:

$$Y_i \in \{\text{Safe,Warning,Dangerous}\} \qquad 2$$

Random Forest is an ensemble-learning method comprising B decision trees. Each individual tree $h_\beta(X)$ casts a vote for the predicted class at input X, and the final prediction $\hat{Y}$ is determined by majority voting:

$$\hat{Y} = \text{mode}\{h_1(X), h_2(X), \ldots, h_B(X)\} \qquad 3$$

In this simulation, B = 100 trees were configured. Node splitting in each decision tree is optimized by minimizing Gini impurity:

$$\text{Gini} = 1 - \sum_{k=1}^{K} p_k^2 \qquad 4$$

where:

K is the number of target classes (K = 3);

and p_k represents the relative frequency of class k in the node.

The reported model evaluation used a test set of 150 simulated samples. Performance was assessed using overall accuracy, class-wise precision, recall, F1-score, the confusion matrix, and feature importance. These measures were used to evaluate overall classification performance, class-specific detection behavior, and the relative contribution of the five input variables.

IV. RESULTS AND DISCUSSION

4.1. Simulation Dataset

A simulated aquarium water-quality dataset was used to evaluate the proposed classification approach. The dataset included five input variables: temperature, pH, turbidity, dissolved oxygen, and water level. Table 1 summarizes the variables and units, while Table 2 provides representative simulated records and their assigned status labels. Because these records are simulated, they should be interpreted as model-development inputs rather than as measurements collected from a physical aquarium.

Table 1. Input variables used in the simulated aquarium water-quality dataset.

No	Variable	Meaning	Unit
1	Temperature	Water temperature in the aquarium	°C
2	pH	pH level of the water	Dimensionless
3	Turbidity	Water turbidity	NTU
4	Dissolved Oxygen	Dissolved oxygen in the water	mg/L
5	Water level	Water level in the aquarium	1: Normal; 0: Low

Table 2. Representative simulated aquarium water-quality data and classification status.

Timestamp	Temperature (°C)	pH	Turbidity (NTU)	Dissolved Oxygen (mg/L)	Water Level	Status
8/10/2026 8:00	27.5	7.1	12	6.5	1 (Normal)	Safe
8/10/2026 10:30	31	6.4	35	4.8	1 (Normal)	Warning

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Timestamp	Temperature (°C)	pH	Turbidity (NTU)	Dissolved Oxygen (mg/L)	Water Level	Status
8/10/2026 13:15	33.5	5.8	70	2.5	0 (Low)	Dangerous
8/10/2026 16:00	29.2	7.6	46	7.4	1 (Normal)	Warning
8/10/2026 18:45	27.7	8.1	38.9	5.8	0 (Low)	Dangerous
8/10/2026 21:00	26.8	7.3	15	6.8	1 (Normal)	Safe
8/11/2026 00:00	25.9	7.0	10	7.0	1 (Normal)	Safe
8/11/2026 03:00	32.0	6.2	42	4.5	1 (Normal)	Warning
8/11/2026 06:00	34.8	5.5	68	2.2	0 (Low)	Dangerous
8/11/2026 09:00	28.3	7.4	20	6.9	1 (Normal)	Safe

4.2. Classification Performance and Confusion Matrix

The test set contained 150 simulated samples distributed among Safe, Warning, and Dangerous classes. As shown in Figure 4, the model correctly classified 54 of 55 Safe samples, all 55 Warning samples, and 37 of 40 Dangerous samples. The four misclassified observations were assigned to the Warning class: one Safe sample and three Dangerous samples. Thus, 146 of 150 test samples were classified correctly, corresponding to an overall accuracy of 97.3%. Importantly, the three Dangerous-to-Warning errors indicate that the model can still underestimate some critical simulated conditions, although none of the Dangerous samples were classified as Safe.

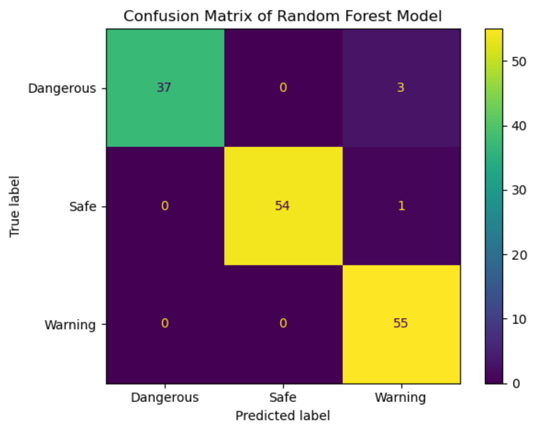

Figure 4. Confusion matrix of the Random Forest model for simulated aquarium water-quality classification.

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The confusion matrix indicates strong separation among the three simulated classes, with perfect recall for Warning and no false-positive predictions for the Dangerous class. However, the remaining Dangerous-to-Warning errors are relevant for a safety-oriented monitoring system and should be examined using real sensor data during future validation.

4.3. Feature Importance Analysis

Feature importance was examined to identify which input variables contributed most strongly to the Random Forest classification decisions within the simulated dataset. The resulting model-derived importance scores are shown in Figure 5.

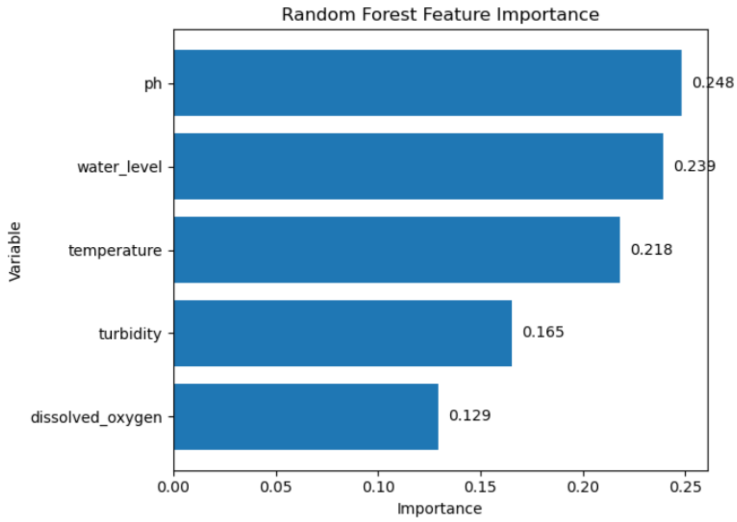

Figure 5. Random Forest feature importance for the simulated aquarium water-quality variables.

The model-derived feature importance scores were:

• pH: 0.248

• Water level: 0.239

• Temperature: 0.218

• Turbidity: 0.165

• Dissolved oxygen: 0.129

Within this simulation, pH, water level, and temperature received the three highest importance scores. These values describe the behavior of the trained model on the simulated dataset and should not be interpreted as empirical or causal rankings of aquarium water-quality factors.

4.4. Model Evaluation

Table 3 summarizes class-specific precision, recall, F1-score, and support. Safe achieved the highest F1-score (0.991), with precision of 1.000 and recall of 0.982. Dangerous achieved precision of 1.000, recall of 0.925, and an F1-score of 0.961. Warning achieved recall of 1.000, precision of 0.932, and an F1-score of 0.965. The overall accuracy was 0.973. These results demonstrate strong internal classification performance on the simulated test set, but they do not establish performance under real aquarium conditions.

Table 3. Classification performance of the Random Forest model on the simulated test set.

Class	Precision	Recall	F1-score	Support
Dangerous	1.000	0.925	0.961	40
Safe	1.000	0.982	0.991	55

Warning	0.932	1.000	0.965	55
Accuracy			0.973	150
Macro average	0.977	0.969	0.972	150
Weighted average	0.975	0.973	0.973	150

The class-level results are consistent with the confusion matrix: the Warning class captured all Warning samples, while the lower recall for Dangerous reflects three Dangerous samples predicted as Warning. Accordingly, the model provides a useful preliminary benchmark for the proposed framework, while experimental validation remains necessary before practical deployment.

4.5. Proposed Hardware Configuration and Control Implications

The Random Forest classifier is intended for future integration with an IoT hardware platform. In the proposed design, a WeMos D1 board based on the ESP8266 would receive sensor data and communicate monitoring results through Wi-Fi. Sensor and actuator modules would then support data acquisition, alerts, and control actions. The present study did not experimentally implement or validate these hardware components; therefore, the configuration described below should be treated as a proposed design rather than a tested prototype [13], [17], [18]

Central processing unit: The proposed design uses a WeMos D1 development board based on the ESP8266 microcontroller, providing integrated Wi-Fi connectivity for IoT communication.

Temperature sensing: A DS18B20 digital temperature sensor is proposed for submerged water-temperature measurement.

Actuators and peripherals: Relay or driver modules are proposed to interface the controller with external devices required for aquarium management.

Automated feeder: A 5 V mini motor driven through an L298N motor-driver module is proposed for controlled feed dispensing.

Cooling system: A TEC1-12706 thermoelectric cooling module, together with a heat sink, fan, and small water pump, is proposed as a possible temperature-control subsystem.

Life support and lighting: The proposed hardware configuration can also include an oxygen pump, water filter, electric heater, and LED lighting system.

4.6. Limitations

This study has three principal limitations. First, the dataset was simulated rather than collected from physical aquarium sensors. Second, the proposed monitoring and control architecture was evaluated only at the simulation level. Third, the reported classification performance and feature-importance scores have not been validated using independent real-sensor data. Therefore, the results should be interpreted as preliminary model-generated evidence, and real-time experimental validation is required before practical application.

V. CONCLUSION

This study presented a simulation-based evaluation of an IoT-enabled aquarium monitoring and control framework using Random Forest classification. Based on five simulated input variables—temperature, pH, turbidity, dissolved oxygen, and water level—the model achieved 97.3% accuracy on a 150-sample test set. The F1-scores were 0.991 for Safe, 0.965 for Warning, and 0.961 for Dangerous. Model-derived feature importance was highest for pH (0.248), water level (0.239), and temperature (0.218). These results indicate strong internal performance on the simulated dataset and support further investigation of Random Forest-based decision support for aquarium monitoring. However, the findings do not constitute experimental validation. Future work should implement the proposed ESP8266/ESP32-based hardware, collect calibrated sensor measurements, and evaluate classification and automated control under real aquarium conditions.

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