

REAL-TIME AQUACULTURE MONITORING SYSTEM USING AIOT TECHNOLOGY

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ABSTRACT

Aquaculture contributes greatly to the overall fish production, but old methods of monitoring water quality prove ineffective and continue to allow high fish mortality and low productivity. This paper presents a Real-Time Artificial Internet of Things (AIoT) Monitoring System for continuous monitoring of critical water parameters in aquaculture that would enhance management parameters such as temperature, turbidity, dissolved oxygen (O₂), pH, CO₂ and water levels. The system represents the integration of many sensors with an ESP8266 microcontroller which transmits data to a cloud-based platform that can be accessed by a mobile application. Machine learning techniques such as Decision Trees, Support Vector Machines, and Logistic Regression will be used to optimize the activation of the used actuators (oxygen generators, feeders, water pumps, and heaters) based on real-time detected measurements from sensors. Experimental results prove that it works; steady monitoring and precise prediction of best water conditions correspond to what is theoretically expected. The AI-powered decision-making framework that curtails energy usage and feed wastage plus guarantees a prompt reaction to changes in the environment renders this a smart aquaculture solution: scalable and cost-effective for modern fish farming while fostering enhanced productivity and sustainability for the aquaculture sector.



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I. INTRODUCTION

In the realm of aquaculture, the preservation of water quality is paramount for sustaining the health and productivity of aquatic organisms throughout their growth cycle [1]. Nevertheless, the existing monitoring techniques in Algeria prove to be largely ineffective, as many farmers depend on traditional methods that demand extensive time, resources, and effort to mitigate aquatic mortality rates [2]. The absence of sophisticated technological instruments for real-time surveillance and informed decision-making only intensifies these difficulties. Despite these setbacks, the aquaculture industry accounts for over 20% of Algeria's overall fish production, underlining its crucial significance. Acknowledging this reality, the Ministry of Fisheries and Fish Production has recently initiated actions aimed at enhancing the sector by dismantling barriers for 105 aquaculture projects and granting concessions to investors interested in establishing or expanding their enterprises. Furthermore, tax benefits have been implemented to stimulate growth in both fishing and aquaculture activities [3], [4]. In order to obtain optimal aquaculture yields, it is crucial to continuously monitor water quality, aquatic health, and feed management in real-time. Conventional methods, that allows farmers to manually assess various parameters, not only prove to be unreliable but also pose risks to safety and hygiene [5-9]. In response to these issues, the present study presented in this paper introduces an innovative solution: an Artificial Intelligent Wireless Internet of Things (AIoT)-based system designed for the remote monitoring of aquaculture. This system seamlessly integrates smart technology to automate the monitoring process, particularly focusing on small and medium-scale fisheries. The main aim is to create a comprehensive AIoT framework for real-time water quality assessment, paired with a mobile application that offers farmers immediate access to essential data. Furthermore, the system is designed to investigate the optimal habitat conditions for freshwater shrimp, enhancing aquaculture practices significantly.

The proposed system uses several kind of components, including the ESP8266 microcontroller, humidity sensors, water-proof temperature sensors, pH sensors, dissolved oxygen sensors, carbon dioxide (CO₂) sensors, turbidity sensors, water level sensors, and actuators. The devices are mounted to measure and transmit data to a cloud-based platform via a wireless internet connection. The information is appeared to farmers using a mobile app, enabling them to monitor water status in real-time and make informed decisions. The system also used an AI model for optimizing the function of actuators, such as water pumps, heaters, oxygen machines, and feeders. This allows the system to either notify farmers to manually adjust water quality or automatically swap devices to optimize water conditions in the fish. Besides, the system uses weather forecasting data to predict water quality variations caused by external factors like rainfall or temperature fluctuation. This feature provides early warnings to farmers that can implement counteractive measures in advance before issues arise. This integration prevents wastage of feed, reduces energy consumption, and offers optimal water quality, offering a wise, responsive, and budget-friendly solution for aquaculture management in current times. The paper is structured in the following order: firstly, we identify the importance of aquaculture in Algeria in the introduction; secondly, we briefly examine studies in aquaculture; thirdly, we describe the proposed solution and utilized materials; fourthly, we discuss findings; and finally, we summarize with lessons and directions for future studies. This breakthrough system is a significant advancement in addressing aquaculture management issues through AIoT and real-time data for enhancing productivity and sustainability in the sector.

II.RELATED WORKS

Fish farmers have traditionally relied on manual methods to monitor water quality in fish ponds, which are often time-consuming and prone to errors. To address these challenges, researchers have developed various technological solutions to automate and enhance the monitoring process. This section discusses the advancements in this field, including recent works that leverage new technologies such as AI and IoT for improving decision and predictive capabilities. The researchers in [10] proposed an automated system to reduce costs and increase yield in fish farming. The system included sensors for temperature and pH monitoring, a feeding mechanism, and CCTV cameras for surveillance. It also utilized SMS services for communication and status updates. Similarly, [11] developed a GSM-based system to alert farmers about deteriorating water quality by monitoring temperature, pH, and dissolved oxygen levels. The system comprised input, evaluation, communication, and output modules. A system developed by [12] utilized the LoRaWAN protocol for wireless communication for long distances, thus perfectly suited for remote fish ponds. It monitored water level and temperature, contained an RTC module for lighting control, and used a buzzer for threshold notification. In [13], a real-time water quality monitoring model was proposed, which utilized IoT and smartphones to gather sensor data. It was useful for farmers to obtain water quality data from distant locations. Similarly, [14] proposed an IoT-based monitoring system for physico-chemical parameters in Pangasius fish farming in the Mekong Delta. Another IoT-based system in [15] used the pH and salinity sensors module and a web-based monitor module for controlling and data visualization. The system in [16] is an aquaculture of shrimp, monitoring parameters like pH, temperature, and dissolved oxygen (DO). It focused on efficient monitoring and control of environmental parameters for the best growth of shrimp. In [17], a Raspberry Pi-based system, sensors, a USB camera, and OpenCV were suggested for water quality monitoring.

Temperature, turbidity, TDS, and color were tracked as parameters. While the system offered remote monitoring via an Android app, it lacked a module for taking corrective action on identifying anomalies. Authors in [18] presented a machine learning (ML)-based framework that predicts water quality parameters such as dissolved oxygen, pH, and temperature from historical data. The framework employed a Random Forest algorithm to provide early warnings and recommendations for rectification. Similarly, in [19] authors developed an AI based Internet of Things system that integrates neural networks to predict algal blooms, which are harmful to fish health. Authors in [20] integrated computer vision and AI to monitor fish behavior as an indicator of water quality. The system used convolutional neural networks to analyze video streams sent from underwater sensors to detect abnormal movement of fish that would signal poor water conditions. The study in [21] introduced an edge AI-driven system for real-time water quality monitoring. The system employed light weight ML models on edge devices to analyse sensor data locally, avoiding latency and cloud computing reliance. The system also provided an actionable insights to farmers via a mobile app. In [22], a hybrid AI-IoT system was suggested for aquaculture monitoring. The system integrated IoT sensors for data acquisition with AI algorithms for anomaly detection and predicting maintenance. the system provides a feedback mechanism to automate the corrective actions, such as water pH adjustment and aerator activation. A new paradigm in [23] integrated block chain technology with AI and IoT to offer data integrity and transparency for water quality monitoring. The system employed smart contracts to automatically validate data and provide a tamper proof history of water quality parameters.

Table 1: Related works comparison.

Ref	Components	Communication Method	Monitoring Aspects	Limitations
[10]	Sensors, CCTV, SMS	SMS	Temperature, pH, water level	Limited to basic parameters
[11]	GSM module, sensors	GSM	Temperature, pH, dissolved oxygen	No corrective action module
[12]	LoRaWAN, RTC, buzzer	LoRaWAN	Water level, temperature	Limited to specific parameters
[13]	IoT sensors, smartphone	IoT	Real-time water quality	Dependent on smartphone availability
[14]	IoT-based system	IoT	Physico-chemical variables	Region-specific (Mekong Delta)
[15]	Sensor module, web-based monitoring	IoT	pH, salinity	Limited control functionality

[16]	Sensors, control module	IoT	pH, temperature, DO	Focused on shrimp farming
[17]	Raspberry Pi, OpenCV, sensors	Wi-Fi/Internet	Temperature, turbidity, TDS, color	No corrective action module
[18]	ML algorithms, IoT sensors	IoT	Predictive monitoring (DO, pH, etc.)	Requires historical data for training
[19]	Neural networks, IoT sensors	IoT	Algal bloom prediction	High computational cost
[20]	CNNs, underwater cameras	Wi-Fi	Fish behavior analysis	Limited to visual indicators
[21]	Edge AI, IoT sensors	Edge computing	Real-time monitoring	Limited to lightweight models
[22]	AI-IoT hybrid system	IoT	Anomaly detection, predictive actions	Complex implementation
[23]	Blockchain, AI, IoT	Blockchain	Data integrity, transparency	High infrastructure cost

Source: Authors, (2026).

In addressing the limitations of existing IoT-based fishpond monitoring systems as illustrated in Table 1, we are trying in our project to focus on providing comprehensive training programs for fish farmers to enhance their technical skills, emphasizing the use of renewable energy sources, and implementing cost-effective solutions to enhance sustainability and affordability [24], [25]. Our proposed system optimizes data collection processes, integrates automation features, and ensures scalability based on modular design approaches to increase system efficiency and adaptability for different fish farming environments. Our developed system monitors various parameters, optimizes the activation of actuators, and offers a user interface for the easy manipulation by farmers, making the system suitable for implementation in different ponds and for several types of fish [26].

III. PROPOSED SYSTEM

This section contains three subsections which are the introduction of required hardware and software technologies used in the proposed system, description of the functionality of the system architecture and its flowchart in order to display the steps and procedures of the system.

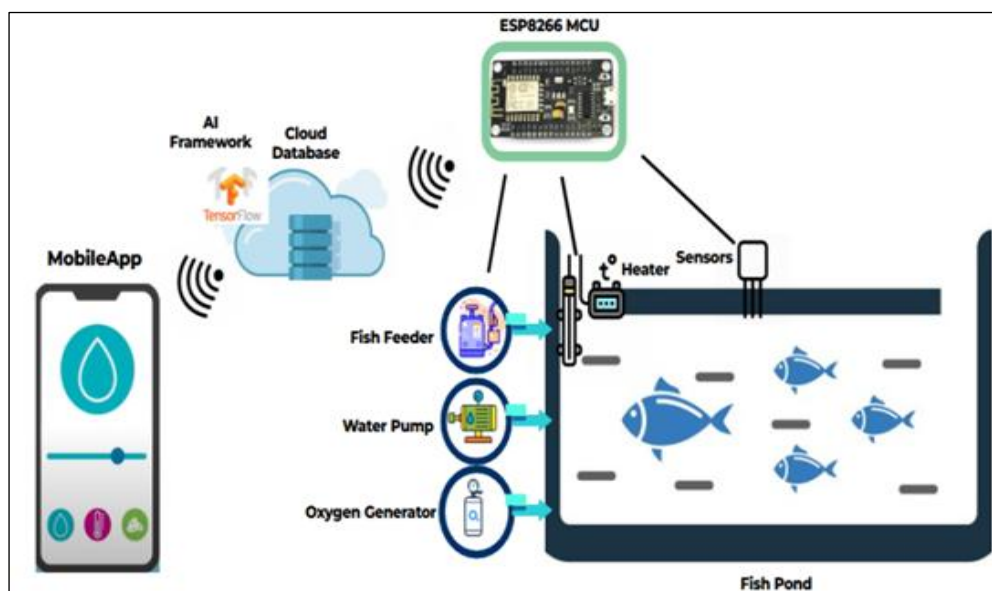


Figure 1: The general scheme of our monitoring system.

Source: Authors, (2026).

This circuit diagram, Fig. 1, shows how the different parts of our water quality monitoring system for a fish farming pond are connected. The system includes: the fish basin where the fish are raised; a set of sensors placed in the water to measure important water quality parameters like temperature, pH, dissolved oxygen, carbon dioxide (CO₂), and turbidity, water level; and a controller (ESP8266) that collects data from the sensors. This data is sent to a mobile app (smartphone) passing by the cloud data base where farmers can see the water conditions in real time. This system contains an AI approach in order to take the optimal decision and optimize the functionalities of actuators (Water pump, Heater, O₂ Generator, and the feeder) the system can either let the farmer know to adjust the water quality manually or automatically turn on devices to keep the water in the best condition for the fish. Additionally, weather forecasting data is integrated to predict changes in water quality caused by factors like rain and temperature changes that allows farmers for early warnings in order take action before problems arise. These features can make the system smarter, more adaptive, and more efficient for modern aquaculture management.

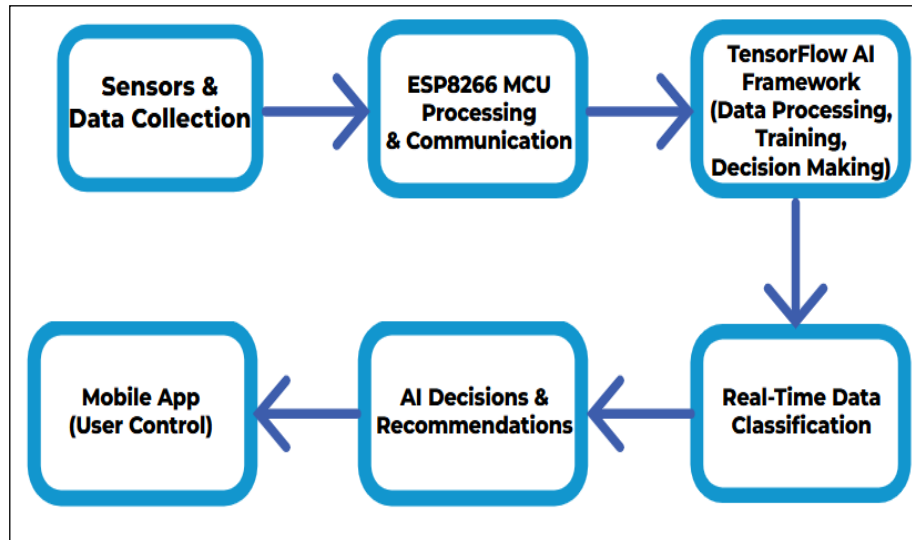


Figure 2: Proposed Flowchart for our fish pond water quality monitoring application.
Source: Authors, (2026).

As shown in Fig. 2, once the data is collected from the sensors such as O₂ levels, water level, turbidity, CO₂, temperature, etc., it is stored in Firebase which is a cloud-hosted NoSQL database server, for processing and analysis. In the cloud based environment, The data undergoes rigorous pre-processing to ensure an optimal quality and relevance of data, a crucial step given the significance of smart aquaculture monitoring systems. The initial phase allows treating missing values, occurred often due of intermittent connectivity or sensor malfunctions. To achieve uniformity in the disparate measurements, data such as temperature, O₂ levels, and turbidity are standardized using Min-Max scaling based on Eq. (1) illustrated bellow used in the Data Preprocessing to justify the scaling of sensor inputs before feeding them into machine learning models [26-28] . Further, categorical variables, like water quality categories or species types, undergo a transformation process called one-hot encoding, making them digestible for machines without implying any ordinal significance. A pivotal step in the preprocessing journey is to divide data into training and test subsets. This division is important to avoid over fitting, a situation where a model can excel on its training data which can fail to classify the unfamiliar data. By training the model on one subset and testing it on an unseen one, a more realistic gauge of the model's performance in real-world aquaculture scenarios is achieved.

Min-Max scaling equation

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where:

x' is the normalized value

x is the raw sensor reading

x_{max} x_{min} are the minimum and the maximum values for that parameter.

Once the data is preprocessed, it is utilized to train the machine learning model using Tensor Flow which is a powerful machine learning framework hosted in the cloud. The tested data used also for model evaluation. The cloud platform also hosts an API for users to access into the functionalities of the system. It saves and manages the system's data in Firebase by ensuring scalability, reliability, and security. Additionally, it can enable integration with other services and applications such as the weather API which provides future weather parameters such as temperature, humidity, wind speed, and precipitation forecasts. These weather insights which are displayed finally in the mobile app allow the farmer taking proactive measures, such as adjusting the site to provide more water and feed in anticipation of adverse weather conditions, ensuring the safety and optimal growth of aquatic life. The cloud platform is a centralized hub for data processing, analysis, and decision making in the smart aquaculture monitoring system. Once the collected sensor data passed by a general analysis process, the system applies machine learning techniques to ensure accurate and efficient monitoring and control decisions. A labeled dataset is then prepared, containing sensor data and corresponding actuator actions such as feeder activation, O₂ generator control, heater adjustment, or water pump operation in order to provide valuable information to know when to activate or deactivate these devices based on sensor readings. The machine learning model, built using TensorFlow, is trained to capture the intricate relationships between sensor readings (e.g., O₂ levels, water temperature, turbidity), weather parameters, and actuator requirements. Sophisticated machine learning algorithms such as decision trees (DT), support vector machines (SVM), or logistic regression (LR) are employed for this purpose. Once the model is trained is then deployed in the cloud platform to enable real time communication for predicting optimal actuator actions based on the learned patterns and relationships. This intelligent decision making system improves resource efficiency, ensures the optimal environmental conditions for aquatic life, and empowers the aqua culturists with precise and real time monitoring and control strategies, even in the face of changing weather conditions .

IV. RESULTS AND DISCUSSIONS

Once we completed the calibration of our sensor, and all the sensors are properly connected to the controller (MCU esp8266), as illustrated in Figure 3 which is the prototype of the system; we initiated the phase of detecting the measurements of the water quality of the basin. The results of this phase are illustrated in Figure 4; this later presents the detected measurements database stored in Firebase.



Figure 3: Installation of Sensors in the pool.
Source: Authors, (2026).



Figure 4: Firebase collected information.
Source: Authors, (2026).

In our application, notifications are generated to inform the user in the following cases: when the water quality does not meet the standard norms for normal fish life, during the automatic activation of pumps or oxygen filter, and in case of any problem detected in the basin. These notifications will be displayed on the farmer's smartphone using a mobile application that we have developed, as illustrated in the Fig. 5.

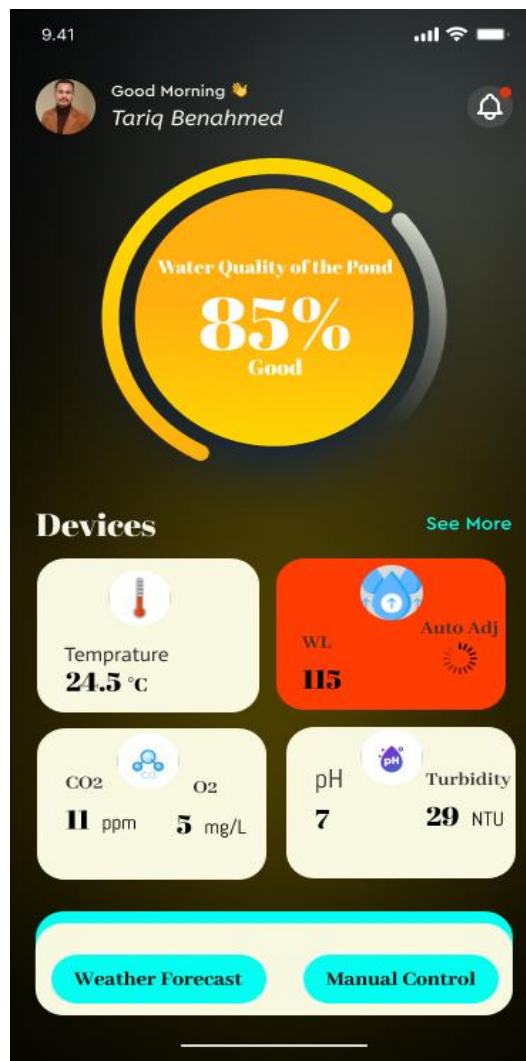


Figure 5: Our mobile application with the set of notifications.
Source: Authors, (2026).

The dataset used in our system includes nine attributes as illustrated in the Table 2 which are O₂ levels, water level, turbidity, CO₂ levels, temperature, feeder activation, heater activation, O₂ generator activation, and water pump activation. all these attributes form the foundation of the dataset used in the smart aquaculture system. after analyzing and making the decisions based on the used data, the system can activate the actuators such as the feeder activation, the O₂ generator control, the heater adjustment, and water pump operation and this ensures optimal conditions for aquatic life, conserves resources and enhances productivity. To maximize the range of measurements and improve the dataset's robustness, we combined two publicly available datasets: IoT Dataset on Water Quality and Tilapia Health in Colombian Aquaculture Ponds and A Simple Dataset of Water Quality in Aquaponic Fish Ponds Based on IoT the both of them is downloaded from Kaggle referenced in [29], [30]. This step allows more comprehensive analysis and finnaly better decision making in the smart aquaculture system. To evaluate the performance of the smart aquaculture monitoring system, the dataset was divided into two subsets: one for training and the other for testing. 80% of the data which is approximately 98,135 samples were used for the training step of the machine learning algorithms, while the remaining 20% that represents approximately 24,534 samples were used for the testing and validation step. This step ensures that the model is trained on the adequate amount of data while maintaining an independent test set to evaluate the generalization capabilities. For the classification tasks the used dataset was more treated to ensure the balanced representation of different classes such as water quality categories and actuator activation states.

Table 2: The used dataset sample.

O ₂ (mg/L)	WL (cm)	Tby (NTU)	CO ₂ (ppm)	Tem (°C)	Feeder Activation (0/1)	Heater Activation (0/1)	O ₂ Generator Activation (0/1)	Water Pump Activation (0/1)
6.2	120.5	15.3	12.4	24.5	1	0	0	0
5.8	118.7	18.7	14.2	23.8	1	0	0	0
7.1	122.0	12.5	10.8	25.2	1	0	0	0
4.9	115.3	22.4	16.5	22.3	1	1	0	0
6.5	119.8	17.8	13.1	24.8	1	0	0	0
5.3	117.2	20.1	15.7	23.5	1	0	0	1
6.8	121.0	14.6	11.9	25.0	1	0	0	0
5.1	116.4	19.3	14.8	22.8	1	1	0	0

Source: [29], [30].

O₂ Levels; represents the dissolved oxygen levels in the water it's in milligrams per liter (mg/L).

Water Level: indicates the level of water in the pond which is measured in centimeters.

Turbidity: Turbidity measures the clarity of the water in order to indicate the presence of suspended particles.

CO₂ Levels: measures the concentration of carbon dioxide inside the water pond and expressed in parts per million (ppm).

Temperature: Temperature refers to the water temperature and measured in degrees Celsius or Fahrenheit.

Feeder Activation: This attribute indicates whether the feeder is activated or not and include details about the amount or timing of feed dispensed represented in binary value.

Heater Activation: This attribute indicates whether the heater was activated and may include details about the duration or intensity of heating represented in binary value.

O₂ Generator Activation: This attribute indicates whether the O₂ generator is activated or not and include details about the duration or intensity of the oxygen generation and represented in binary value.

Water Pump Activation: This attribute indicates whether the water pump is activated or not and may include details about the duration or flow rate of water circulation and represented in binary value.

After implementing the intelligent actuator control mechanism in our system it can effectively optimizes water quality conditions in real time. The AI-driven approach ensures that critical parameters are continuously monitored and adjusted as needed, in this part we present some key relationship points that the system based on to take the optimal decisions;

1. Feeder Activation
 - Temporarily activated every 2 hours unless turbidity is high.
 - If turbidity > 20 NTU, feeder is deactivated 0 until water pond is clean.
2. Water Pump Activation
 - Activated 1 if turbidity is greater than 20 NTU or water level is less than 115 cm.
3. O₂ Generator Activation:
 - Activated 1 if O₂ levels is less than 5 mg/L.
4. Heater Activation:
 - Activated 1 if temperature is less than 22°C.

When comparing the performance of decision trees (DT), logistic regression (LR), and support vector machines (SVM) for the aquaculture system, their performance was evaluated based on accuracy, precision, recall, and F1 score. The experimental evaluation method used was the confusion matrix, as shown in table 3 for the decision tree classifier. The evaluation metrics were computed from the confusion matrix.

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

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

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

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

Where:

TP (True Positive): Correctly classified positive cases.

TN (True Negative): Correctly classified negative cases.

FP (False Positive): Incorrectly classified negative cases.

FN (False Negative): Incorrectly classified positive cases.

Table 3: Confusion Matrix of DT in Water Pump Activation.

	Predicted: No Water Pump Activation	Predicted: Water Pump Activation
True: No Water Pump Activation	TN = 72	FP = 4
True: Water Pump Activation	FN = 9	TP = 41

Source: Authors, (2026).

Table 4: Summarizes the performance measures of the different classification models.

ML Model	Accuracy	Precision	Recall	F1 Score
LR	0.8514	0.9189	0.7391	0.8192
DT	0.8968	0.9111	0.82	0.8631
SVM	0.8415	0.8571	0.7317	0.7894

Source: Authors, (2026).

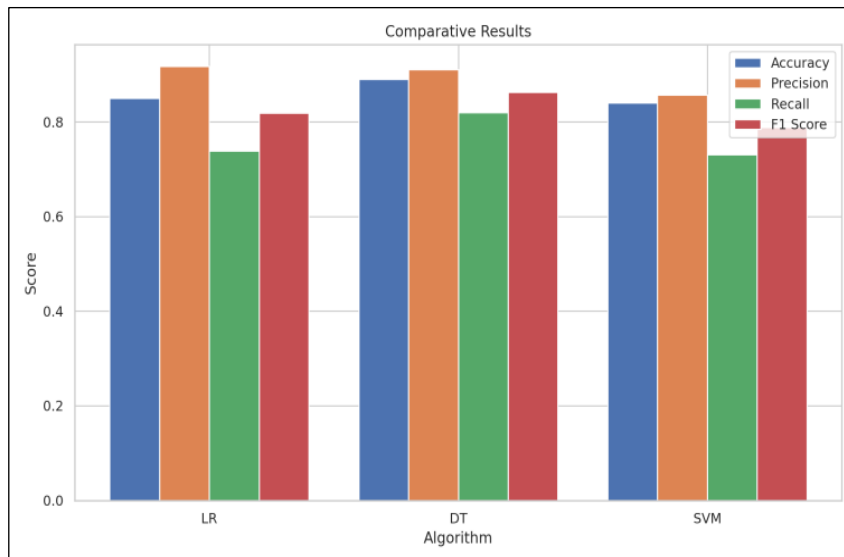


Figure 6: Comparative results of the used Algorithms.

Source: Authors, (2026).

Basing on the comparison illustrated in the Fig. 6 and Table 4, the decision tree model shows a better performance by achieving high accuracy, precision, recall, and F1 score calculated by Eq. (2,3,4 and 5), as shown in Figure 3. In the development of our smart aquaculture system using IoT and machine learning techniques, the decision tree classifier played an important role in decision-making processes by achieving the highest performance. In this work various training parameters can be adjusted to refine the performance of decision trees for that we relied on the default parameters to guarantee consistency and replicability specifically the criterion for the quality of a split is set to "gini" which is a measure used to measure the impurity of the data illustrated in Eq. (6), the maximum depth of the tree was left undefined (allowing the tree to expand until all leaves are pure), the minimum samples split is set to 2 and the minimum samples leaf is set to 1. By employing these default values the foundational benchmark for the system's performance is established, which can serve as a reference point for future iterations and optimizations.

$$\text{Gini} = 1 - \sum_{i=1}^n p_i^2 \quad (6)$$

Where:

p_i is the probability of class i at a given node.
 n is the number of classes.

Among the three used models, decision trees has shown a better performance than SVM and logistic regression due to their ability to manipulate non linear relationships in the used water quality data by providing clear decision rules and interpretable feature importance scores unlike SVM, which is functioning as a black box. decision trees provide an obvious transparency in decision making steps such as activating the O₂ generator when oxygen levels is under below 5 mg/L. Additionally, DT is more efficient than SVM in term of computation which requires complex kernel optimization. Logistic Regression struggled with the multi class nature of actuator activation while DT managed it with an effective way. Furthermore, DT achieved a higher recall (82%), making it more reliable in detecting critical water conditions and reducing fish mortality, whereas SVM had difficulties generalizing due to imbalanced data.

Table 5: Summarizes the water quality improvements before and after implementing the AI based IoT system.

Parameter	Before AI IoT System	After AI IoT System	Recommended Range
Temperature (°C)	27 - 34	29 - 31	20 - 35
pH Level	5.8 - 7.2	6.5 - 8.0	6.5 - 9.0
Dissolved O ₂ (mg/L)	2.5 - 4.0	4.2 - 5.5	3.0 - 5.0
CO ₂ Levels (ppm)	>15	<10	<10
Turbidity (NTU)	>50	20 - 30	30 - 80

Source: Authors, (2026).

Table 5 shows key water quality parameters such as Temperature (°C), pH Level, Dissolved Oxygen (mg/L), CO₂ Levels (ppm), and Turbidity (NTU) prior to and after implementing our AIoT system and their recommended ranges. The findings obtained affirm significant improvements here we can see that temperature stabilizes in a narrower range (29°C to 31°C), stabilizes pH levels at a better range (6.5 to 8.0), and raises dissolved oxygen levels significantly (4.2 mg/L to 5.5 mg/L). Furthermore, CO₂ levels were reduced to less than 10 ppm, at the recommended level, with turbidity reducing to 20–30 NTU, well below the best optimal range. These results show the effectiveness of the proposed AIoT system which uses real time monitoring, advanced analytics, and automated control systems to optimize water quality. Through solving issues such as low oxygen levels, elevated levels of CO₂, and unstable pH and temperature, the system ensures compliance with recommended standards while fostering a more sustainable and healthier aquatic ecosystem, exemplifying the paradigmatic transformative potential of AIoT technologies for environmental control.

V. CONCLUSIONS

In this paper, a sophisticated AIoT-based real-time aquaculture monitoring system is proposed that overcomes the limitations of the current water quality monitoring systems. With the use of a mixture of several sensors, an ESP8266 microcontroller, a cloud-based system, and machine learning algorithms, the system effectively monitors the key parameters such as temperature, turbidity, dissolved oxygen, pH, CO₂ level, and water level. The use of AI-based decision-making optimizes the driving of actuators, reducing power usage, eliminating waste in feed, and allowing proactive reactions to environmental variations. The results obtained in the experimental part demonstrate the efficiency of our system suggested with a view to ensuring water quality stability, in particular high oxygen levels, pH constancy, and CO₂ level. Compared to other solutions, the advantages of our solution are real-time automatic monitoring, predictive analytics based on AI, as well as simplicity of access through mobile devices. Among the compared machine learning models, Decision Tree classifier is the most accurate in order to optimize actuator operation. In addition, the integration of weather forecasting information with the system's capabilities helps to predict earlier and give timely notifications to the farmers. In the future works and in order to enhance the proposed system by introducing more advanced AI models such as deep learning for improved predictive analytics and anomaly detection. We can also thinking to add a system for observing fish behavior with computer vision methods to enhance decision making.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

Methodology: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

Investigation: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

Discussion of results: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

Writing – Original Draft: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

Writing – Review and Editing: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

Resources: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

Supervision: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

Approval of the final text: Benahmed Tariq, Seddiki Nouredine and Benahmed Khelifa.

VII. REFERENCES

- [1] Aquaculture: levée d'obstacles sur 105 projets, Algérie Eco, Mar. 16, 2022. [Online]. Available: <https://www.algerie-eco.com/2022/03/16/aquaculture-levee-dobstacles-sur-105-projets/>. [Accessed: May 11, 2024].
- [2] M.M. Islam, M.A. Kashem, and F. Jui, "Aqua fishing monitoring system using IoT devices," *International Journal of Innovative Science, Engineering and Technology*, vol. 6, no. 11, pp. 109–114, 2019.
- [3] A. Ramya, R. Rohini, and S. Ravi, "IoT based smart monitoring system for fish farming," *International Journal of Engineering and Advanced Technology*, vol. 8, no. 6S, 2019.
- [4] W. Sung, J. Chen, and H. Wang, "Remote fish aquaculture monitoring system based on wireless transmission technology," in *Proc. Int. Conf. Information Science, Electronics and Electrical Engineering*, Sapporo, Japan, pp. 540–544, 2014..
- [5] D. Prangchumpol, "A model of mobile application for automatic fish feeder aquariums system," *International Journal of Modeling and Optimization*, vol. 8, pp. 277–280, 2018.
- [6] T. Joseph et al., "Aquaculture monitoring and feedback system," in *Proc. IEEE Int. Symp. Smart Electronic Systems (iSES)*, Rourkela, India, pp. 326–330, 2019.
- [7] I. Ullah and D. Kim, "An optimization scheme for water pump control in smart fish farm with efficient energy consumption," *Processes*, vol. 6, p. 65, 2018.
- [8] K. Preetham, B.C. Mallikarjun, K. Umesh, F.M. Mahesh, and S. Neethan, "Aquaculture monitoring and control system: An IoT based approach," *International Journal of Advanced Research Ideas and Innovative Technology*, pp. 1167–1170, 2019.
- [9] A. Karali and F. Echikh, *L'aquaculture en Algérie, Mémoire de fin d'étude pour l'obtention du diplôme d'ingénieur d'État en sciences de la mer*, Institut des Sciences de la Mer et de l'Aménagement du Littoral, 2004.
- [10] .E. Idachaba, J.O. Olowoleni, A.E. Ibhaze, and O.O. Oni, "IoT Enabled Real-Time Fishpond Management System," 2017.
- [11] B.D. Sri, K. Nirosha, P. Priyanka, and B. Dhanalaxmi, "GSM based fish monitoring system using IoT," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 8, no. 7, pp. 8, 2017.
- [12] S. Nocheski and A. Naumoski, "Water monitoring IoT system for fish farming ponds," *International Scientific Journal "Industry 4.0"*, vol. 3, no. 2, pp. 77–79, 2018.
- [13] S.A. Obado, *IoT Based Realtime Fish Pond Water Quality Monitoring Model*, Master's Thesis, Strathmore University, 2019.
- [14] V.Q.D. Luong et al., "Design and deployment of an IoT-based water quality monitoring system for aquaculture in Mekong Delta," *International Journal of Mechanical Engineering and Robotics Research*, vol. 9, no. 8, pp. 1146–1150, 2020.
- [15] Periyadi et al., "IoT-based guppy fish farming monitoring and controlling system," *TELKOMNIKA Telecommunication, Computing, Electronics and Control*, vol. 18, no. 3, pp. 1538–1545, 2020.
- [16] L. Ashok Kumar et al., "Aquaculture monitoring system using IoT," *International Research Journal of Engineering and Technology (IRJET)*, vol. 8, no. 4, 2021.
- [17] S. Senthilrani et al., "IoT based aquaculture monitoring system," *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering*, vol. 9, no. 4, 2021.
- [18] J. Smith et al., "Machine learning for predictive water quality monitoring in aquaculture," *Journal of Aquaculture Technology*, 2022.
- [19] H. Lee et al., "Neural network-based algal bloom prediction in aquaculture," *Aquacultural Engineering*, 2023.
- [20] Y. Zhang et al., "Computer vision-based fish behavior analysis for water quality assessment," *Sensors*, 2023.
- [21] R. Kumar et al., "Edge AI for real-time water quality monitoring in aquaculture," *IEEE Internet of Things Journal*, 2023.
- [22] S. Patel et al., "Hybrid AI-IoT systems for smart aquaculture monitoring," *Aquaculture Research*, 2023.
- [23] T. Nguyen et al., "Blockchain-enabled AI-IoT systems for transparent aquaculture monitoring," *Journal of Cleaner Production*, 2023.
- [24] A. Bhatnagar and P. Devi, "Water quality guidelines for the management of pond fish culture," *International Journal of Environmental Science*, vol. 5, no. 2, 2019.
- [25] U. Darmalim et al., "IoT solution for intelligent pond monitoring," in *Proc. 3rd Int. Conf. on Eco Engineering Development (ICEED)*, 2020.
- [26] M. Chiu et al., "Development of smart aquaculture farm management system using IoT and AI-based surrogate models," *Journal of Agriculture and Food Research*, vol. 9, p. 100357, 2022.
- [27] O.O. Olanubi, T.T. Akano, and O.S. Asaolu, "Design and development of an IoT-based intelligent water quality management system for aquaculture," *Journal of Electrical Systems and Information Technology*, vol. 11, no. 1, pp. 1–23, 2024.
- [28] S. Panda, R. Narayanamoorthi, and S. Dhanalakshmi, "Advanced real-time monitoring system for marine net pens: integrating sensors, GPRS, GPS, and IoT with embedded systems," in *Proc. Int. Conf. on Micro-Electronics and Telecommunication Engineering*, Singapore, pp. 419–435, 2023.
- [29] *IoT Monitoring of Water Quality and Tilapia*, Kaggle Dataset. [Online]. Available: <https://www.kaggle.com/datasets/jocelyndumlao/iot-monitoring-of-water-quality-and-tilapia>. [Accessed: Feb. 11, 2025].
- [30] *Small Aquaculture Fishpond Dataset*, Kaggle Dataset. [Online]. Available: <https://www.kaggle.com/datasets/bobsis/small-aquaculture-fishpond/code>. [Accessed: Feb. 11, 2025].