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Biofloc Fish Farming

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Abstract- *Biofloc technology is increasingly recognized as an eco-friendly and space-saving approach to aquaculture, especially beneficial in areas where water availability is limited. By delivering real-time notifications, it improves overall system management and efficiency. . However, its operation is performance of biofloc fish farming while reducing fish mortality and highly sensitive to variations in water quality parameters such economic losses. The results demonstrate that integrating IoT with as, ammonia levels, turbidity, machine learning can transform small-scale aquaculture into a moredata-driven and sustainable sector. and temperature. This study proposes a cost-efficient, solar- powered IoT system for monitoring biofloc aquaculture tanks,*

which utilizes machine learning techniques to detect fish mortality at an early stage.

Designed for low-income fish farmers in southern Punjab, Pakistan, the system continuously measures critical water quality parameters using affordable sensors connected to Arduino UNO and NodeMCU ESP8266 microcontrollers.

Over a period of 1.5 months, data was collected at two-minute intervals and uploaded to the ThingSpeak cloud platform. After preprocessing and balancing the dataset using ADASYN, many ML algorithms—including Random Forest, XGBoost, A number of machine learning models were developed and evaluatedsuch as Naïve Bayes, decision tree models, and support vector machine techniques. Among these, Random Forest and XGBoost performed better, predicting fish.

Keywords- Biofloc Technology, Internet of Things (IoT), Machine Learning, Fish Mortality Prediction, Smart Aquaculture, Tilapia Farming

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I. INTRODUCTION

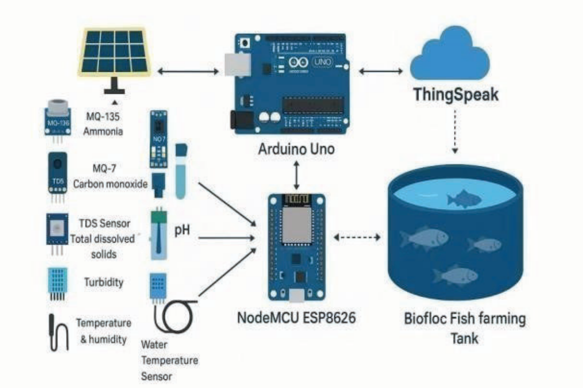

Figure 1: System Architecture

Figure 1: System Architecture

Global malnutrition remains a pressing issue, particularly in low-income and developing regions. Fish, a valuable protein source that is essential to support reliable food availability and adequate nutritional intake. As conventional fish farming methods struggle with land and water limitations, Biofloc technology has emerged as a promising alternative. It offers sustainable aquaculture by recycling waste nutrients, reducing water consumption, and increasing fish yield in limited space. Yet, this system is highly sensitive to water quality parameters such as pH, ammonia, dissolved oxygen, turbidity, and temperature. Minor deviations in these values can significantly affect fish health and lead to high mortality rates.

In Pakistan, especially in the underdeveloped regions of southern Punjab, traditional biofloc farming lacks automation and is labor-intensive. Fish farmers often struggle to monitor key water parameters manually, resulting in delayed interventions and preventable losses. The absence of predictive tools and real-time data further exacerbates the risk of sudden fish deaths, undermining the profitability and sustainability of biofloc farming.

The Internet of Things (IoT) has greatly improved modern agriculture by enabling real-time monitoring through networked sensors and cloud platforms.IoT systems can process sensor-generated data to find patterns when combined with machine learning (ML) approaches. and forecast unfavorable outcomes—such as fish mortality—by analyzing past data and relationships between different environmental factors.

This research addresses the gap by developing a lowcost, solar-powered IoT-based smart monitoring system tailored for biofloc tanks in rural Pakistan. Integrated with ML models, captures real-time data on water quality and predicts fish mortality 1–2 hours in advance, allowing for timely intervention.

Objectives of the Study

- To design and implement a cost-effective, solar powered IoT-based water monitoring system for biofloc tanks.
- To gather real-time sensor readings of important water quality parameters affecting Tilapia fish during a crucial growth stage.
- To clean, preprocess, and balance the collected dataset using methods such as ADASYN to improve the accuracy of prediction models
- To develop and assess Several machine learning are applied to accurately forecast fish mortality.
- To identify the major environmental factors linked to fish mortality and provide meaningful insights to support fish farmers in better management decisions.

Novel Contributions

- Development of a low-cost, solar-powered, real-time IoT monitoring system using Arduino and NodeMCU.
- Data collection and analysis during a high-risk aquaculture period (May–July), with over 18,000 sensor readings.
- are applied to estimate fish mortality with accuracy reaching 98%.
- Deployment of a correlation matrix to evaluate the influence of water parameters on fish mortality.
- Introduction of a scalable early-warning system that enables fish farmers to take corrective actions before mass mortality occurs.

II. METHODS

2.1 System Architecture

The designed solution integrates affordable sensing devices with IoT- based tools to track and forecast water conditions in biofloc aquaculture systems. The complete structural layout of the system is depicted in Figure 1 (to be included).
The device runs continuously thanks to a solar energy source and a 16-hour backup battery.
A Node MCU ESP8266 WiFi module sends data collected by the Arduino UNO microcontroller from several sensors to the Thing speak cloud server every two minutes.

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Sensors deployed:

• MQ-135: Determines the concentration of ammonia
• MQ-7: Quantifies carbon monoxide
3 The concentration of dissolved solids in the water is monitored using a TDS sensing device.
• pH Sensor: Determines the acidity or basicity of water
• Turbidity Sensor: Determines how clear the water is
• DHT11: Monitors humidity and ambient temperature
• Water Temperature Sensor: This device gauges the temperature of tank water.

3.2 Data Collection

Data collection is over a 1.5-month period from May 13 to July 2, 2023, which is a critical growth phase for Tilapia fish. The system collected readings at two-minute intervals, resulting in 18,978 sensor.

3.3 Data Preprocessing

The dataset was prepared for machine learning analysis by performing the following preprocessing steps.

- Missing values were handled by dropping entries with sensor calibration delays.
- Special characters (e.g., “\r\n” in water temperature) were cleaned.
- Categorical encoding: “Mortality” (Yes/No) was converted to binary (1 = Yes, 0 = No).
- Standardization: All sensor values were scaled to zero mean and unit variance.
- Data splitting: The dataset was split into training and testing sets using different ratios (60–40, 70–30, 80–20, 90–10).

Since the number of “mortality = 1” instances was significantly lower, Adaptive Synthetic Sampling (ADASYN) was applied to balance the dataset. This ensured that the minority class (fish deaths) had sufficient representation during training, avoiding biased model performance.

3.4 Machine Learning Models

Six supervised machine learning classifiers were implemented to estimate fish mortality using various water condition parameters indicators.

1. Decision Tree
2. Random Forest
3. Support Vector Machine (SVM)
4. Logistic Regression
5. Gaussian Naïve Bayes
6. XGBoost

Every model underwent training through 10-fold cross-validation, utilizing various splits of the dataset. Metrics like accuracy, precision, recall, and F1- score were performance.

3.5 Cloud Infrastructure

Data was uploaded to the ThingSpeak cloud platform, which provided:

- Free storage for up to 8,200 entries/hour
- Public dashboard for visualizing water parameters in real-time
- Easy integration with ESP8266 for data push

III. RESULTS

This evaluation trained using the processed dataset. To ensure the reliability and stability of the models, several train–test data splits were applied. The effectiveness four key metrics. F1-score, accuracy, precision, and recall.

3.1 Model Performance on 60–40 Train-Test Split

Table 1 shows the results of all six machine learning classifiers trained on 60% of the data and tested on the remaining 40%.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Random Forest	97	95	99	97
Decision Tree	97	95	99	97
Support Vector Machine	94	89	99	94
Logistic Regression	93	93	89	91
XGBoost	97	95	99	97
Gaussian Naïve Bayes	91	89	92	90
combined model learning	96	94	99	96

Table 1: Evaluation Results (60–40 Split)

3.2 Performance on 70–30 and 80–20 Splits

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Tables 2 and 3 present the performance results obtained from the 70–30 and 80–20 training–testing data splits.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
a tree-based learning	98	97	99	98
XG Boost	97	96	99	97
Decision Tree	96	96	96	96
SVM	95	91	99	95
Logistic Regression	94	94	91	92
Gaussian Naive Bayes	91	90	92	91
Ensemble Learning	97	95	99	97

Table 2: Evaluation Results (70–30 Split)

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Random Forest	97	96	98	97
XGBoost	97	96	98	97
Decision Tree	95	95	95	95
SVM	95	93	98	95
Logistic Regression	93	93	91	94
Gaussian Naïve Bayes	90	91	89	90
Ensemble learning	97	95	98	97

Table 3: Evaluation Results (80–20 Split)

3.3 Correlation Analysis

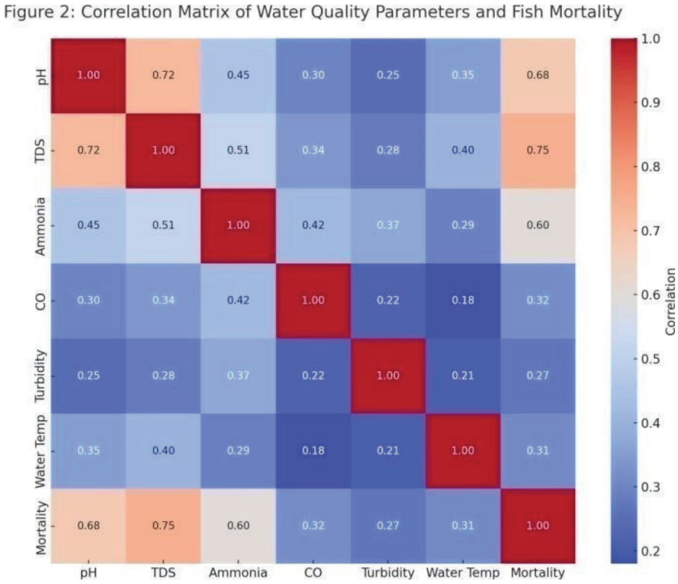

Figure 2: Correlation matrix illustrating fish mortality.

To identify the water quality factors that have the greatest influence fish mortality, a correlation matrix was computed.

Figure 1 (to be inserted) shows that pH and TDS had the strongest with fish mortality. Ammonia showed moderate correlation. In comparison, less significant associations were noted between CO, turbidity, and water temperature, indicating that ammonia, TDS, and pH serve as more significant control parameters.

3.4 Accuracy Comparison Graph

Figure 2 (to be inserted) illustrates a visual comparison of the classification accuracy achieved by different machine learning models across various training and testing splits. The consistent performance of Random Forest and XGBoost highlights their effectiveness across all configurations.

3.5 Summary of Results

- Random Forest and XGBoost
- Key influencing parameters: pH, TDS, and Ammonia.

IV. DISCUSSION

The machine learning approaches. The integration of IoT-based sensor networks greatly improves monitoring and safety.

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decisionmaking capabilities of biofloc fish farming. The system's ability to predict fish mortality up to 1–2 hours in advance is a major breakthrough for small-scale farmers in resourceconstrained environments like southern Punjab, Pakistan.

4.1 Interpretation of Key Results

Among the tested machine learning classifiers, Random Forest and XGBoost consistently achieved superior and train-test splits, with accuracy levels reaching 98%. These ensemble methods excel due to their ability to handle high-dimensional data and reduce overfitting through model averaging or boosting strategies.

Precision and recall values above 95% suggest that these models are reliable in both correctly identifying actual mortality risks and avoiding false positives, which is essential for real-time alert systems in fish farming. On the contrary, models like Naïve Bayes underperformed, likely due to the assumption of feature independence, which is not suitable for multivariate and correlated water quality data. The correlation analysis further confirms that pH level, TDS and ammonia levels are identified as key indicators of fish mortality. These results are consistent with previous aquaculture studies, which indicate that fluctuations in these parameters can place stress on fish physiology and raise the likelihood of death.

4.2 Practical Implications for Fish Farmers

In traditional biofloc setups, water quality monitoring is manual, time-consuming, and reactive rather than proactive. When values surpass mortality criteria, our IoT-based technology generates early warning signals and offers continuous, real-time insights into water conditions.

The system's low cost (~$60) and use of solar power make it ideal for adoption in rural or off-grid locations. For comparison, the cost of fish seed for 500 Pangasius fish is approximately $174—thus, even a single mortality event prevented can yield substantial savings and protect farmer income.

The system also reduces dependency on skilled labor or manual vigilance, empowering local communities with minimal technical knowledge to manage fish health more effectively.

4.3 Comparison with Related Work

While previous studies have proposed IoT-based aquaculture systems, few have achieved the combination of:

- Low-cost hardware integration
- Advanced predictive capabilities using ML
- Focused application to specific fish species and regions

For example, Md. Rashid et al. (2021) implemented a KNN-based a framework designed to forecast water conditions, though it reported only 77.3% accuracy. Similarly, Mahmuda et al. (2021) used image processing and achieved moderate prediction success. In contrast, the current study not only achieves up to 98% prediction accuracy but also incorporates a comprehensive real- time IoT framework and a long-term dataset.

4.4 Limitations

Despite its success, the study has some limitations:

- The system is calibrated specifically for Tilapia in the southern Punjab region; results may vary with other species or environmental conditions.
- Data was collected over a limited 1.5-month period, focused on a specific growth phase.
- There are access restrictions (8200/hour) on the Thing Speak cloud utilized for data transmission, which could impede scalability.
- Environmental sensors (like DHT11) may provide reduced precision compared to high-end industrial systems.

These limitations provide opportunities for further improvement and development in future research.

CONCLUSION AND FUTURE WORK

This study presents a cost-effective, IoT- and machine learning-based a smart monitoring solution designed for biofloc-based fish farming, specifically addressing the requirements of small-scale aquaculture in southern Punjab, Pakistan. The system continuously monitors critical water quality parameters— such as pH, total dissolved solids (TDS), ammonia, turbidity, and temperature—using affordable, solar-powered sensors and microcontrollers.

The data collected over 1.5 months was processed and used to train multiple supervised machine learning models. Among the tested models, Random Forest and XGBoost consistently demonstrated superior performance, achieving prediction accuracies of up to 98% for fish mortality. A strong association fish deaths and several key environmental factors.

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TDS, and ammonia levels validates the system's predictive capacity.

By providing 1–2 hours of advance warning, the system enables fish farmers to take proactive measures, reducing mortality, improving yields, and minimizing economic loss. Additionally, its low cost (~$60) and solarpowered design make it accessible and sustainable for farmers in remote or underserved areas.

Future Work

While the current system is optimized for Tilapia fish, future research will aim to:

- Extend the solution to support multiple fish species, each with distinct environmental tolerances.
- Collect year-round data to improve prediction reliability across different seasons.
- Integrate edge computing for offline prediction and real-time alerts without full cloud dependency.
- Develop mobile or SMS-based alert systems for farmers with limited internet access.
- Implement ensemble learning techniques and deep learning models for further accuracy improvements.

This research sets the foundation for transforming biofloc aquaculture from a manual, reactive system into a data-driven, intelligent practice, especially in low-resource contexts.

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