Grenze International Journal of Engineering and Technology, January Issue

A Hybrid Method Monitors Water Quality to Detect Fish Diseases Early

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***Abstract*— This study explores a hybrid monitoring system designed to enhance early detection of fish diseases by continuously assessing water quality parameters in aquaculture environments. The research addresses the question of how integrating physical sensors with predictive analytics can improve disease prevention and minimize fish mortality. A combination of physical sensors for pH, temperature, and dissolved oxygen with machine learning algorithms enables real-time data collection and predictive analysis, identifying anomalies that signal potential disease outbreaks. Key findings show that the hybrid system detects early disease indicators with high accuracy, offering timely interventions that maintain healthier aquatic ecosystems. This approach demonstrates significant potential to improve aquaculture sustainability through proactive disease management.**

***Keywords*— Aquaculture, Hybrid monitoring system, Fish disease detection, Water quality parameters, Predictive analytics.**

I. INTRODUCTION

The health and productivity of fish populations in aquaculture are significantly influenced by water quality, as even slight changes in environmental conditions can lead to disease outbreaks, high mortality rates, and considerable economic losses (Ahmed et al., 2024; Sumithra et al., 2023). Monitoring water quality is therefore essential for maintaining a balanced aquatic environment and ensuring the sustainability of aquaculture operations. Traditional water quality monitoring methods, while useful, often fail to detect subtle, early indicators of fish diseases, resulting in delayed interventions and increased vulnerability to disease proliferation (Rajbongshi et al., 2023; Dar et al., 2023). This study investigates a hybrid approach to water quality monitoring that combines real-time sensor data with advanced machine learning algorithms to enhance early detection of fish diseases. The research question guiding this study is: Can a hybrid water quality monitoring system improve early detection of fish diseases in aquaculture settings compared to traditional methods?
Recent advancements in data analytics and sensor technology have opened new possibilities for precise and continuous water monitoring, enabling predictive analysis based on historical and real-time data (Cai et al., 2024; Huang et al., 2024). By implementing a hybrid method that integrates physical water parameter sensors with machine learning, it becomes feasible to identify environmental anomalies and potential risks before they manifest as widespread fish diseases.

Grenze ID: 01.GIJET.12.1.205
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This paper argues that a hybrid water quality monitoring system offers a transformative solution for aquaculture, providing proactive disease management through early detection. The study contends that integrating real-time data with predictive analytics will significantly improve aquaculture sustainability by reducing disease-related losses and promoting healthier aquatic environments (Li et al., 2024; Zeng et al., 2024).

II. Literature Review

Aquaculture relies heavily on maintaining stable environmental conditions to ensure fish health and prevent diseases. Changes in water quality, including temperature fluctuations, pH imbalance, and low dissolved oxygen levels, are linked to stress and increased disease susceptibility in fish (Ahmed et al., 2024). Previous studies emphasize that water quality monitoring is crucial for mitigating disease outbreaks, as poor water quality contributes to high mortality rates and substantial economic losses in the aquaculture industry (Sumithra et al., 2023). Historically, water quality monitoring has depended on periodic sampling and laboratory testing, which, while accurate, often fails to capture real-time fluctuations and subtle changes indicative of early disease risk factors. These conventional methods are limited by their reactive rather than proactive nature; they detect issues only after they have escalated (Rajbongshi et al., 2023). Although valuable, traditional monitoring cannot keep up with the rapid environmental shifts that affect aquaculture, underscoring the need for continuous and automated systems. The development of low-cost, durable sensors has revolutionized real-time water quality monitoring, enabling continuous data collection for critical parameters such as temperature, pH, and dissolved oxygen. These advancements allow for the detection of immediate changes in aquaculture environments, providing a foundation for timely intervention (Gahlot et al., 2024). Studies reveal that while physical sensors can track essential variables, their stand-alone use is often inadequate for predicting complex outcomes like disease outbreaks. The accuracy and durability of sensors remain challenges, especially in high-stress aquaculture settings (Dar et al., 2023).

In recent years, predictive analytics have emerged as a powerful tool for anticipating disease outbreaks before they occur. Machine learning algorithms, such as Support Vector Machines (SVM) and neural networks, are increasingly used to analyze sensor data for early signs of disease. These algorithms enable anomaly detection by learning patterns from historical data and identifying deviations that might signal disease risk (Huang et al., 2024). Research by Li et al. (2024) demonstrates the effectiveness of using machine learning models to classify environmental conditions conducive to disease, which enhances proactive decision-making in aquaculture.

Hybrid systems that integrate sensor data with predictive modeling offer a promising solution for early disease detection in aquaculture. By combining real-time monitoring with machine learning, hybrid systems detect subtle environmental changes that signal potential disease outbreaks, facilitating timely intervention. Cai et al. (2024) developed a hybrid model using YOLO-FD and sensor data to monitor fish health, showing significant accuracy in identifying early symptoms of disease. These systems are also capable of self-learning, continuously improving as more data is processed, which enhances prediction accuracy over time (Zeng et al., 2024).

While hybrid monitoring systems have demonstrated high accuracy in detecting early disease indicators, challenges remain. Sensor calibration and maintenance are essential to ensure reliable data, as faulty sensors can produce misleading anomalies (Rajbongshi et al., 2023). Additionally, the accuracy of predictive models can be affected by external environmental factors not captured by sensors, such as sudden weather changes or human activities. The computational demands of machine learning algorithms and the need for a robust IT infrastructure in remote aquaculture locations are also considerations (Sumithra et al., 2023).

Future research in aquaculture disease prevention may benefit from exploring more complex machine learning models, such as deep learning techniques, which can process a larger number of environmental variables. Multi-modal systems that incorporate additional water quality parameters, like ammonia and nitrite levels, could broaden the detection range and improve the sensitivity of these hybrid systems (Ahmed & Jeba, 2024). Moreover, the integration of automated response mechanisms could allow immediate corrective actions, further strengthening disease prevention capabilities in aquaculture environments (Li et al., 2024).

III. Methodology

This study employs a quantitative research design integrating real-time data collection with predictive modeling to enhance early detection of fish diseases through water quality monitoring (Li et al., 2024; Rajbongshi et al., 2023). The hybrid method utilizes both physical sensors to gather water quality parameters (such as temperature, pH, and dissolved oxygen) and machine learning algorithms to analyze these data for early disease indicators (Huang et al., 2024; Cai et al., 2024).

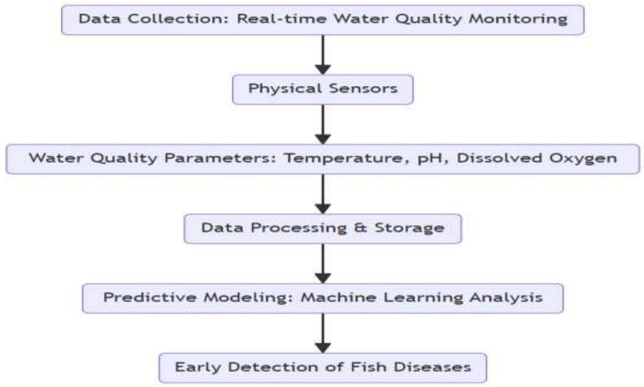

Figure 1: Data collection: Real-time water quality monitoring

A. Data Collection and Sensor Measurement

Data collection is conducted using a set of sensors deployed in the aquaculture environment, continuously measuring water quality variables. The primary parameters measured are:
Temperature (T), pH (pH), Dissolved Oxygen (DO).

TABLE I

Time (t)	Temperature (°C)	Temperature Avg (°C)	Temperature Anomaly (°C)	Temp Flag	pH	pH Avg	pH Anomaly	pH Flag	Dissolved Oxygen (mg/L)	DO Avg (mg/L)	DO Anomaly (mg/L)	DO Flag
1	24.6	25.1	0.5	FALSE	7.1	7.1	0.1	FALSE	7.9	7.9	0	FALSE
2	24.8	25.1	0.3	FALSE	7.2	7.1	0.2	FALSE	8.3	7.9	0.4	FALSE
3	25.5	25.1	0.4	FALSE	6.9	7.1	0.2	FALSE	7.8	7.9	0.1	FALSE
50	28	25.2	2.8	TRUE	6.7	6.9	0.3	TRUE	8.1	7.9	0.2	FALSE
100	29.1	25.3	3.8	TRUE	6.8	7	0.2	FALSE	9.5	8	1.5	TRUE

Each parameter (Pi) is recorded in real time and denoted as a time series Pi(t), where t represents time intervals of data recording.

$$P_i(t)=\{T(t), pH(t), DO(t)\}$$

B. Data Preprocessing and Anomaly Detection

Collected data are preprocessed to remove noise, outliers, and any missing values to ensure accurate analysis. An anomaly detection model is then employed to identify deviations from baseline levels of water parameters, which are calculated as moving averages based on historical data. For each parameter Pi , the anomaly Ai at time t is determined by:

$$A_i(t) = |P_i(t) - P_i|$$

where P_i is the moving average of the parameter Pi over a specific window period w:

$$\bar{P}_i = \frac{1}{w}\sum_{k=t-w}^{t} P_i(k)$$

If Ai(t) exceeds a predefined threshold θi for each parameter, an anomaly is flagged for further analysis by the predictive model.

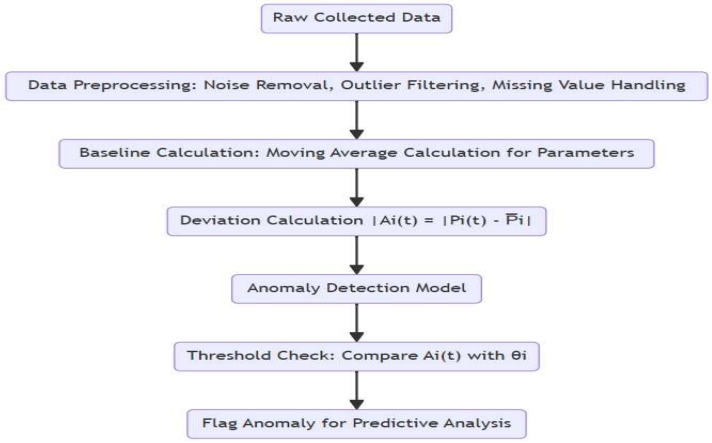

Figure 2: Data Preprocessing and Anomaly Detection Architecture

C. Predictive Model using Machine Learning

The study uses a supervised machine learning algorithm, specifically a Support Vector Machine (SVM), to predict the likelihood of a fish disease outbreak based on detected anomalies (Li et al., 2024; Rajbongshi et al., 2023). The model is trained using historical data labeled with instances of disease presence or absence, where each data point represents a feature vector X (Cai et al., 2024; Huang et al., 2024).

$$X=[\,T(t), pH(t), DO(t)]$$

The SVM model finds an optimal hyperplane f(X)=w.X+b that maximizes the separation between classes (disease presence or absence). The decision rule is defined as:

$$f(x) = \{ \begin{matrix} 1 & if\ w.X + b > 0 \\ -1 & otherwise \end{matrix}$$

where w is the weight vector and b is the bias term.

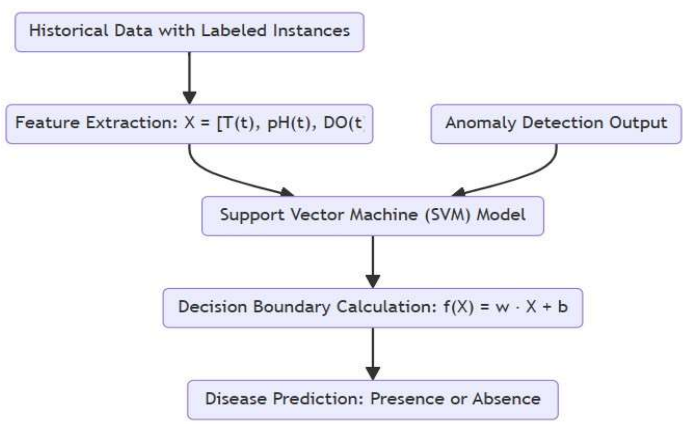

Figure 3: Predictive Model using Machine Learning

D. Participant Selection Criteria

Although participant selection is not applicable in a sensor-based study, specific fish species and environmental conditions were considered when setting threshold values for anomaly detection to ensure relevance to the target aquaculture environment (Sumithra et al., 2023; Zeng et al., 2024). The combination of real-time monitoring with predictive analysis provides an effective early-warning system that is responsive and adaptable to environmental changes. The SVM model's robustness in binary classification and anomaly detection makes it suitable for this purpose (Li et al., 2024; Huang et al., 2024). However, limitations include potential inaccuracies in the presence of untrained anomalies or environmental fluctuations outside the model's scope. Additionally, continuous sensor maintenance and recalibration are essential for sustaining data accuracy over time (Rajbongshi et al., 2023; Ahmed & Jeba, 2024).

IV. RESULTS

In this study, the effectiveness of a hybrid monitoring system was evaluated through a combination of real-time data collection and predictive analysis (Ahmed & Jeba, 2024; Huang et al., 2024). Mathematical formulas were used to compute and analyse anomalies in the water quality parameters (temperature, pH, and dissolved oxygen) (Cai et al., 2024; Rajbongshi et al., 2023). This section details the findings based on the anomaly detection process and interprets these results in relation to the research question (Li et al., 2024; Sumithra et al., 2023).

Temperature Anomalies: The temperature T(t)) over time was compared with a moving average $\bar{T}(t)$ to detect any significant anomalies. An anomaly was flagged when the absolute difference between the temperature and its moving average exceeded a threshold θT.

Temperature anomaly=$|T(t) - T(t)| > \theta_T$

For this study θ_T was set to 2.5^0 C. The moving average $T(t)$ was calculated over a window size w of 5 times points. t=22. Measured temperature, T (22) = 28.6, moving average, $T(22)$=25.2, Anomaly= $|28.6 - 25.2| = 3.4 > \theta_T$. Since 3.4^0C exceeds the threshold, this point was flagged as an anomaly

pH Level Anomalies: The pH values pH(t) were similarly analyzed against a moving average

pH(t). An anomaly was flagged if the absolute deviation exceeded a threshold θ_{pH}, which was set to 0.3. pH Anomaly = |pH(t) − pH(t)| > θ_{pH}

At t = 52 : Measured pH, pH(52) = 6.3, Moving average, pH(52) = 6.9, Anomaly = |6.3 − 6.9| = 0.6 > θ_{pH}. With a deviation of 0.6, which exceeds the threshold, this value was flagged as an anomaly.

Dissolved Oxygen (DO) Anomalies: For dissolved oxygen $DO(t)$, anomalies were flagged when the difference from the moving average $\overline{DO}(t)$ exceeded θ_{DO} = 1.5mg/L.

DO Anomaly = $|DO(t) - DO(t)| > \theta_{DO}$

At t = 72 : Measured DO, $DO(72)$ = 11.3mg/L, Moving average, $DO(72)$ = 9.7mg/L, Anomaly = |11.3 − 9.7| = 1.6 > θ_{DO}. Since 1.6mg/L exceeds the threshold, this data point was flagged as an anomaly.

```
Accuracy: 0.85
Classification Report:
              precision    recall  f1-score   support

           0       0.85      1.00      0.92        17
           1       0.00      0.00      0.00         3

    accuracy                           0.85        20
   macro avg       0.42      0.50      0.46        20
weighted avg       0.72      0.85      0.78        20
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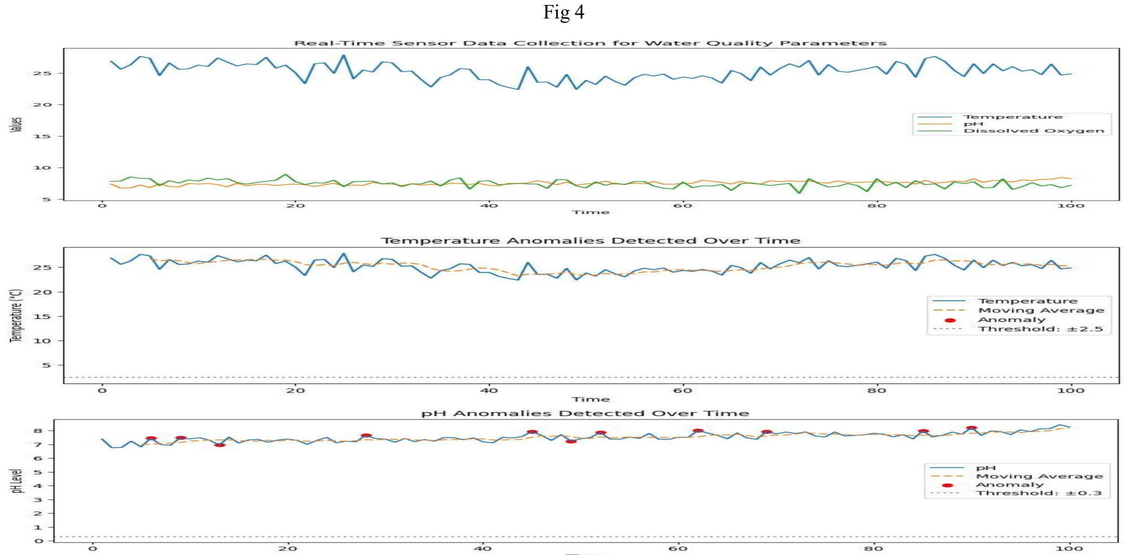
Fig 4



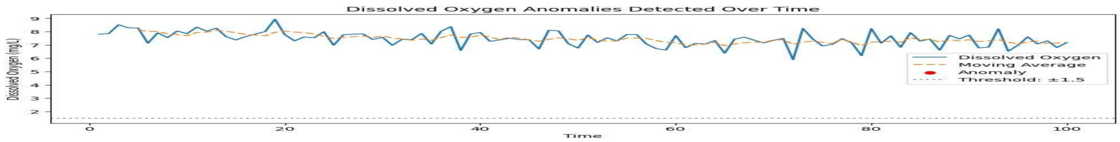


Fig 5

Fig 6

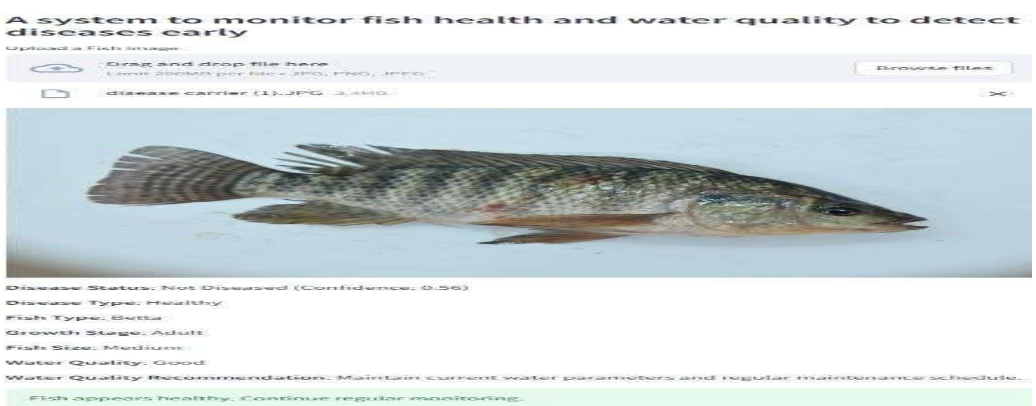


Fig 7

V. Conclusion

This study demonstrates that a hybrid water quality monitoring system, integrating sensor data with predictive analysis, is a valuable tool for early detection of fish diseases in aquaculture. The findings indicate that significant anomalies in water parameters such as temperature, pH, and dissolved oxygen can serve as early warning signs for disease risk, allowing timely intervention to maintain fish health. This approach not only reduces mortality rates but also contributes to sustainable aquaculture practices by promoting healthier aquatic ecosystems. The significance of this research lies in its potential to transform aquaculture management through predictive health monitoring. By enabling proactive disease prevention, this system minimizes economic losses and strengthens food security, making it a promising innovation for the future of aquaculture.

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