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Original Research Article

A Deep Learning Architecture for Smart Fish Farm Management and Early Mortality Prediction

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KEYWORDS

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Smart Fish Farming.

ABSTRACT

The rapid growth of aquaculture has intensified the need for intelligent, data-driven systems capable of improving fish farm productivity, sustainability, and operational efficiency. Traditional manual management approaches remain limited by labor intensity, inconsistent monitoring, and delayed decision-making, especially in dynamic aquatic environments. This study presents a Deep Learning–based Fish Farming Management System that integrates Internet of Things (IoT) sensing technologies with a Bidirectional Long Short-Term Memory (BiLSTM) network to provide real-time monitoring, predictive analytics, and intelligent decision support. IoT-enabled sensors continuously capture water quality and behavioral parameters, which are transmitted to a centralized data-processing architecture for storage, analysis, and automated alerts. The BiLSTM model primarily focuses on fish mortality classification, where it analyzes temporal patterns in environmental and behavioral data to predict mortality risk with high reliability. In addition, the system supports auxiliary predictive and recommendation functions, including anomaly detection and rule-assisted recommendations for feeding, aeration, and environmental adjustments, which are derived from learned temporal trends and domain constraints rather than independently optimized predictive models. Experimental results for the mortality classification task demonstrate outstanding performance, with the model achieving 96.55% accuracy, 96.97% precision, 96.67% recall, a Cohen's Kappa score of 0.9482, and an average AUC of 0.9947, significantly outperforming benchmark models.

CITATION

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INTRODUCTION

Fish farming, or aquaculture, remains a vital contributor to global food security and economic development, particularly in communities that rely heavily on aquatic food sources. As the demand for fish continues to grow, the aquaculture industry is increasingly challenged to enhance productivity, sustainability, and operational efficiency. Traditional fish farming practices, which are often labor-intensive and manually managed, face limitations in precision, consistency, and scalability. This has spurred interest in leveraging intelligent technologies to automate and optimize farm management processes.

Recent developments in data mining and machine learning (ML) have opened new frontiers in aquaculture. Gladju, Kamalam, and Kanagaraj (2022) highlighted how ML frameworks are now being applied in fish health monitoring, environmental control, and production forecasting—marking a shift toward intelligent aquaculture systems. Li and Du (2022) expanded on this by exploring the integration of deep learning and machine vision in tasks such as species identification and behavior recognition, showing the capability of artificial intelligence (AI) to transform aquacultural operations through real-time analysis and control. Chiu et al. (2022) demonstrated the implementation of a smart aquaculture farm management system using Internet of Things (IoT) technologies and AI-based surrogate models to optimize feeding and environmental conditions. This was complemented by the work of Kaur et al. (2023), who reviewed recent progress in deep learning frameworks for precision fish farming, pointing out the increasing demand for autonomous and adaptive control systems in the industry.

Building on these efforts, Dhinakaran, Gopalakrishnan, and colleagues (2023) introduced an IoT-enabled environmental control system integrated with sensors and machine learning for real-time decision-making. Their study underscores the growing reliance on intelligent algorithms to mitigate water quality issues and disease outbreaks. While traditional supervised learning models have shown promise, they often lack the adaptability required in dynamic aquaculture environments where conditions change rapidly and continuous decision-making is essential.

Deep Learning (DL), a subset of machine learning that combines reinforcement learning with deep neural networks, addresses this limitation by enabling systems to learn optimal control strategies through trial and error in real-time environments. In 2024, Abid et al. developed a smart Biofloc monitoring system using IoT and ML, illustrating the integration of intelligent control in water management. Lim (2024) emphasized the transformative potential of AI technologies—including DL, big data, IoT, and robotics—in achieving intelligent, autonomous aquaculture systems capable of learning from complex environments. Furthermore, Hemal et al. (2024) introduced the Aquabot system, which recommends fish farming actions based on continuous monitoring and AI-powered analytics. In light of these innovations, this study proposes the design and implementation of a software system for fish farming management using Deep Reinforcement Learning. Unlike traditional machine learning models, DL offers adaptive, real-time decision-making capabilities, making it suitable for dynamic aquaculture settings. The system aims to support intelligent feeding, environmental monitoring, and operational efficiency—ultimately contributing to the development of smart and sustainable fish farming practices. The fish farming industry plays a crucial role in global food security and economic development. However, traditional fish farm management methods continue to face significant challenges, limiting their potential for productivity, sustainability, and profitability. The reliance on manual monitoring of key factors such as fish behavior, growth patterns, water quality, and feeding schedules remains labor-intensive, time-consuming, and prone to human error. As highlighted by Li & Du (2022), manual processes can lead to inefficiencies such as overfeeding, water pollution, disease outbreaks, and suboptimal growth, all of which increase operational costs and reduce overall yield. While automation technologies and sensor-based systems have been introduced to alleviate these issues, existing solutions still struggle with real-time adaptability and decision-making capabilities. As Li et al. (2022) pointed out, many systems rely on static thresholds and predefined rules, which fail to account for the highly dynamic and complex nature of aquaculture environments. These limitations hinder the widespread adoption of such systems in smaller-scale fish farms. Additionally, Kaur et al. (2023) noted that even advanced systems integrating Artificial Intelligence (AI) and Machine Learning (ML) models often require high-quality data inputs, sophisticated hardware, and intensive human supervision, making them impractical for smaller or resource-constrained farms. Recent advancements in Deep Learning (DL), as explored by Sung et al. (2023), present an opportunity to overcome these challenges. DL-based systems can autonomously adapt to real-time changes in the farm environment by learning from interactions with it, making them ideal for dynamic and unpredictable settings like fish farming. However, as highlighted by Chahid et al. (2022) and Shreesha et al. (2023), the practical integration of DL into fish farming management software remains largely unexplored, with many existing models still struggling with issues such as computational complexity, large data requirements, and lack of real-world validation. Furthermore, while Chiu et al. (2022) and Kristmundsson et al. (2023) demonstrated the potential of combining ML with optimization techniques like Bayesian optimization and echosounder technology, there remains a significant gap in combining these approaches with DL in a comprehensive, real-time system. Existing literature underscores the promise of integrating IoT-based monitoring systems with AI to optimize farm operations, but practical implementations remain limited due to infrastructure constraints and the complexity of combining these technologies (as highlighted by Lan et al. (2022)). Therefore, there is an urgent need for the design and implementation of a software system for fish farming management that incorporates real-time IoT-based monitoring with DL algorithms. This system must be capable of autonomously making decisions regarding critical farm operations—such as feeding, water quality control, and growth optimization—while being accessible, scalable, and suitable for deployment in various aquaculture settings. Bridging this gap can help improve efficiency, reduce waste, and foster sustainable practices in the aquaculture industry, as emphasized in the works of Nazmi et al. (2023) and Abid et al. (2024). The integration of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) technologies has significantly transformed aquaculture, enabling efficient management, monitoring, and prediction systems. Various studies have demonstrated the effectiveness of these technologies, while also highlighting their limitations and implementation challenges. Li & Du (2022) pioneered the use of Convolutional Neural Networks (CNNs) for fish detection and classification. This foundational work introduced CNNs as a tool for automating aquaculture tasks, providing strong evidence for the power of deep learning in aquaculture. However, the model's dependence on high-quality image inputs could limit its generalization in real-world applications with varying image quality. Hu et al. (2022) applied CNNs to automate fish feeding based on visual cues. The system showcases the potential for real-time, vision-based feeding automation, an important area in precision aquaculture. However, the requirement for high-resolution images limits its practical applicability, especially in environments with less-than-ideal camera setups. Chahid et al. (2022) used Q-learning to monitor fish growth trajectories, exploring the potential of reinforcement learning in decision-making systems. The use of Q-learning opens up possibilities for dynamic and real-time growth monitoring. However, the model's success depends heavily on accurate data and the ability to adjust to environmental changes, which can be challenging in dynamic aquaculture settings. Chen et al. (2022) extended CNNs to detect underwater anomalies, contributing to automated surveillance. The application of CNNs for anomaly detection enhances security and monitoring capabilities. However, like other CNN-based methods, the model requires high-quality data, which may not always be available in field conditions. Chiu et al. (2022) used deep learning combined with Bayesian optimization to optimize feeding and environmental conditions. The combination of deep learning with Bayesian optimization makes this approach highly adaptive and efficient for optimizing multiple variables simultaneously. However, the complexity of the implementation may hinder real-world adoption, especially in smaller-scale farms with limited computational resources. Liu et al. (2022) applied YOLO v4 for real-time fish locomotion detection. YOLO v4's efficiency in real-time object detection is a key benefit for monitoring fish movements in dynamic environments. However, the need for substantial computational power and high-quality video feeds may limit its deployment in resource-constrained settings. Lan et al. (2022) evaluated digital twin architectures to improve farm management Digital twin technology offers a comprehensive and data-driven approach to farm management, enabling more precise decision-making. However, practical implementation remains complex and requires a robust infrastructure, which can be costly and difficult to maintain. Li et al. (2022) explored ML methods for water quality prediction, contributing to the optimization of aquaculture environments.ML-based water quality prediction is essential for maintaining optimal conditions in fish farms, potentially improving yields and sustainability. However, the lack of clear algorithmic frameworks and performance evaluations limits the practical utility of this work. Kaur et al. (2023) reviewed the use of deep learning models like CNN and LSTM for fish classification and behavior monitoring. The review provided a comprehensive look at deep learning models, highlighting their high accuracy in specialized tasks. However, the models reviewed demand large datasets and substantial computational resources, making them less accessible for smaller operations. Gladju et al. (2022) provided an overview of AI applications in fisheries. This broad review helped in understanding AI's diverse potential across fisheries and aquaculture. However, the lack of empirical performance data made the findings less actionable for practical implementations. Nazmi et al. (2023) conducted a comparative analysis between machine learning and statistical models for marine fish production forecasting. The study offered valuable insights into the comparative performance of different modeling approaches. However, the analysis raised concerns about the generalizability of the models across different aquaculture systems and environments. Çakir et al. (2023) assessed the performance of various classifiers (RFerns, Naive Bayes, SVM, kNN) for aquaculture applications. The evaluation of multiple classifiers provided a well-rounded understanding of their applicability in aquaculture contexts. However, the study highlighted that classifier performance is highly dataset-dependent, which may limit the applicability of results across diverse settings. Kristmundsson et al. (2023) integrated multibeam echosounders with ML for fish activity monitoring. The novel combination of sensor technologies and ML provided a promising approach to passive monitoring. However, the reliance on specialized echosounders may limit the scalability of this system in smaller or less technologically equipped farms. López-Barajas et al. (2023) used deep learning for fish net inspection and hole detection, pushing forward automation in infrastructure management. The use of deep learning for infrastructure inspection is an exciting application that reduces human labor and increases operational efficiency. However, the method's success depends on the availability of high-quality images, and the system may struggle in non-ideal

conditions. Sung et al. (2023) combined Deep Learning and data fusion for intelligent aquaculture monitoring. The model's use of reinforcement learning for real-time optimization is an innovative approach to aquaculture management. However, high data requirements and the need for constant system updates make this approach challenging for practical deployment. Khan & Byun (2023) introduced a hybrid model combining genetic algorithms with ensemble methods to predict dissolved oxygen levels. The hybrid approach improves accuracy in dissolved oxygen prediction, a critical factor in maintaining optimal fish farming conditions. However, the model may require extensive tuning and validation for various environments, limiting its generalizability. Dhinakaran et al. (2023) developed an IoT-based environmental control system for fish farms. The real-time sensor integration with machine learning provides valuable insights for dynamic environmental control. However, the system lacks specific algorithmic depth and performance evaluations, limiting its applicability in real-world farms. Shreesha et al. (2023) used deep learning to identify fish behavior patterns, offering real-time behavior analysis. The ability to detect and classify fish behavior using deep learning can significantly enhance farm management. However, the system's dependency on large labeled datasets and computational resources limits its feasibility for small farms. Isaac et al.
(2023) proposed an ensemble hybrid approach with Support Vector Regression (SVR) and K-Nearest Neighbors Regression (KNR) the study shows better results in comparison to the single model. Islam et al. (2023) predicted fish species survival using IoT and ML sensors, addressing an important area of farm sustainability. The system can predict species survival with high accuracy, helping to optimize farm operations. However, like many IoT-based systems, this one requires substantial infrastructure and may not be cost-effective for small-scale farms. Ubina et al. (2023) proposed an AIoT-based digital twin system for intelligent fish farming. The integration of AI and IoT provides a holistic approach to farm management, offering a promising path toward fully automated farms. However, the system demands robust infrastructure and high investment, making it impractical for small or medium-sized farms. Capetillo-Contreras et al. (2024) offered a systematic review of AI applications for water quality optimization in aquaculture. The review contributed a valuable compilation of research on AI's role in maintaining optimal water quality. However, the lack of empirical validation leaves a gap in understanding the real-world effectiveness of these AI applications. Mandal and Ghosh (2024) reviewed the role of AI in sustainable aquaculture. Their work provided a comprehensive understanding of AI's potential for sustainability in aquaculture. However, the lack of specific methodologies and performance evaluations makes it difficult to apply their insights practically. Lim (2024) discussed the integration of robotics, big data, and other technologies in aquaculture. This holistic approach offers a broad perspective on how various technologies can be integrated for better farm management. However, the absence of specific algorithms or implementations limits its practical value for researchers or practitioners. Hemal et al. (2024) proposed the Aquabot system, which achieved 94% accuracy in fish species recommendation using ensemble methods. The system's high accuracy in species recommendation offers a practical solution for farm management. However, the model's complexity and the need for substantial computational power may limit its adoption in less technologically advanced settings. Abid et al. (2024) introduced a bioflick monitoring system that integrates real-time water analysis using sensors and machine learning. The system's real-time capabilities are crucial for effective bioflick management and maintaining water quality. However, the lack of algorithmic detail and performance data limits the practical application of the system. Xi et al. (2023) proposed an innovative prawn farm management system using smart headsets and Machine Learning. The integration of smart devices and ML offers an exciting new direction for prawn farm management. However, performance metrics were not clearly defined, making it difficult to assess the real-world applicability of the system. Despite the usefulness of Howarth et al.'s (2025) decision support system (DSS), several limitations restrict its effectiveness in complex, real-world aquaculture settings. Firstly, the reliance on a generalized linear modelling (GLM) framework with logistic regression makes the system inherently linear and limited in handling complex, non-linear relationships among variables. The model's use of lagged mortality as a predictor result in reactive forecasting, meaning it often responds only after a mortality trend has already begun. Additionally, the narrow scope of predictors—mainly temperature, feeding rate, and mortality—fails to capture other critical factors such as pathogen presence, dissolved oxygen, ammonia levels, or fish behaviour patterns. The manual selection of features and thresholds further introduces bias and reduces adaptability. Furthermore, the model's transferability is limited, as it is tailored to a specific dataset and environment, requiring recalibration for new locations or species. In conclusion, the body of research reveals significant progress in applying AI, ML, and IoT to aquaculture. Despite demonstrated advances such as high accuracy, real-time monitoring, and automation, many studies face challenges related to algorithmic specificity, empirical performance data, and practical feasibility. Bridging these gaps through rigorous empirical validation and the development of lightweight, generalizable models remains a key direction for future research.

MATERIALS AND METHODS

The proposed Fish Farming Management System is a smart, integrated software solution that leverages the Internet of Things (IoT) and BiLSTM to improve the efficiency, productivity, and sustainability of aquaculture operations. The proposed Fish Farming Management System is a smart, integrated software solution that leverages the Internet of Things (IoT) and Bidirectional Long Short-Term Memory (BiLSTM) networks to provide real-time monitoring, predictive analytics, and intelligent decision support for aquaculture operations is shown in Figure 1 below.

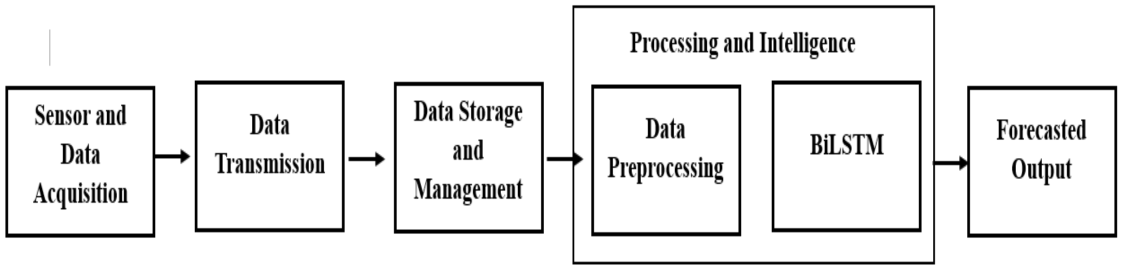

Figure 1: Architecture of the proposed model

Architecture Components

The architecture is composed of five main layers:

Sensor and Data Acquisition Layer

This layer consists of distributed IoT-enabled sensors deployed in fish ponds or tanks to continuously measure key environmental and biological parameters. These include water temperature, pH level, dissolved oxygen, ammonia concentration, turbidity, feeding activity, and fish movement. The sensors collect time-series data at regular intervals and transmit it to the edge or cloud infrastructure.

Data Transmission Layer

Data collected from the sensors is transmitted through wireless communication protocols such as Wi-Fi, Lora WAN, or Zigbee. A gateway device aggregates sensor data and ensures secure transmission to the cloud server or local data processing unit. This layer also handles data validation, time synchronization, and initial filtering to remove outliers or missing values.

Data Storage and Management Layer

All sensor data, historical records, and user inputs are stored in a centralized database system either in the cloud or on-premises based on system requirements. This layer manages structured and unstructured data, ensuring high availability, scalability, and data integrity. Metadata related to fish stock, feeding schedules, water treatments, and disease reports are also stored here.

Processing and Intelligence Layer

This is the core analytical engine of the system, powered by a Bidirectional Long Short-Term Memory (BiLSTM) network. The BiLSTM model is trained on historical aquaculture data and real-time sensor inputs to learn complex temporal patterns and predict future events such as disease outbreaks, water quality degradation, and optimal feeding or harvesting times. The bidirectional structure allows the model to capture dependencies from both past and future time steps, enhancing prediction accuracy.

This layer also supports:

1. Anomaly detection using statistical thresholds and AI-based classifiers
2. Adaptive decision-making for feeding, aeration, or water exchange
3. Model retraining and fine-tuning with new data to improve system performance

User Interface and Visualization Layer

This layer provides an intuitive dashboard for farm managers and operators to monitor real-time data, receive alerts, and view predictive insights. Key features include:

1. Graphical visualization of water parameters and fish behavior
2. Alerts and notifications for critical events (e.g., low oxygen levels)
3. Recommendations for feeding, harvesting, or intervention
4. Customizable reporting tools and trend analysis

This multi-layered architecture enables the Fish Farming Management System to operate as an intelligent, scalable, and user-friendly solution. By integrating IoT-based real-time sensing with the predictive power of BiLSTM, the system supports efficient resource utilization, enhances fish health and survival, and improves overall farm productivity.

Data Collection

The dataset utilized in this study was sourced from the secondary dataset used in the work of Howarth et al. (2025) which includes operational data collected from high-flow Chinook salmon farms between 2017 and 2022. The dataset encompasses a wide range of variables relevant to fish health and farm productivity. These include daily mortality counts, environmental parameters such as water temperature and oxygen saturation, as well as stocking-related data such as biomass, average fish weight, and stocking density. Feeding rates were also recorded. To enhance data quality and reduce the influence of short-term fluctuations or measurement inconsistencies, the raw data were aggregated on a weekly basis.

Implementation Design of the BiLSTM

The predictive model employed in this study is based on a Bidirectional Long Short-Term Memory (BiLSTM) neural network architecture. This design is particularly well-suited for time-series data typical of aquaculture operations, as it captures temporal dependencies from both past and future data sequences. The BiLSTM network was implemented using the TensorFlow deep learning framework. Key hyperparameters of the model were optimized through a grid search and cross-validation approach to maximize predictive accuracy and generalizability. The final configuration included are included in Table 1.

Table 1: Training Parameters of BiLSTM

Parameter	Value
Number of hidden layers	2 BiLSTM layers
Units per layer	64 and 32 LSTM cells respectively
Dropout rate	0.3 (to prevent overfitting)
Batch size	32
Epochs	100
Activation function	ReLU (for dense layers), Sigmoid (for binary classification output)
Loss function	Binary Cross-Entropy
Optimizer	Adam optimizer (learning rate = 0.001)

The training algorithm used was backpropagation through time (BPTT), with the Adam optimizer facilitating efficient gradient descent. Early stopping was also employed to halt training once validation loss ceased to improve, thereby preventing overfitting and ensuring model generalization. For model training and validation purposes, the dataset was partitioned into training and testing subsets, with 70% of the data used for training and 30% reserved for testing. This split helps ensure robust and unbiased performance evaluation of the predictive model. This implementation enabled the BiLSTM model to effectively learn complex temporal patterns in aquaculture data and deliver accurate predictions of mortality trends and other critical farm outcomes.

RESULTS AND DISCUSSION

Graphical output of predicted results such as fish mortality trends, population estimates, and survival probabilities. Graphs and charts are displayed using libraries like Chart.js or D3.js. The core BiLSTM model is implemented and trained using fish population datasets. It predicts future mortality or population levels.

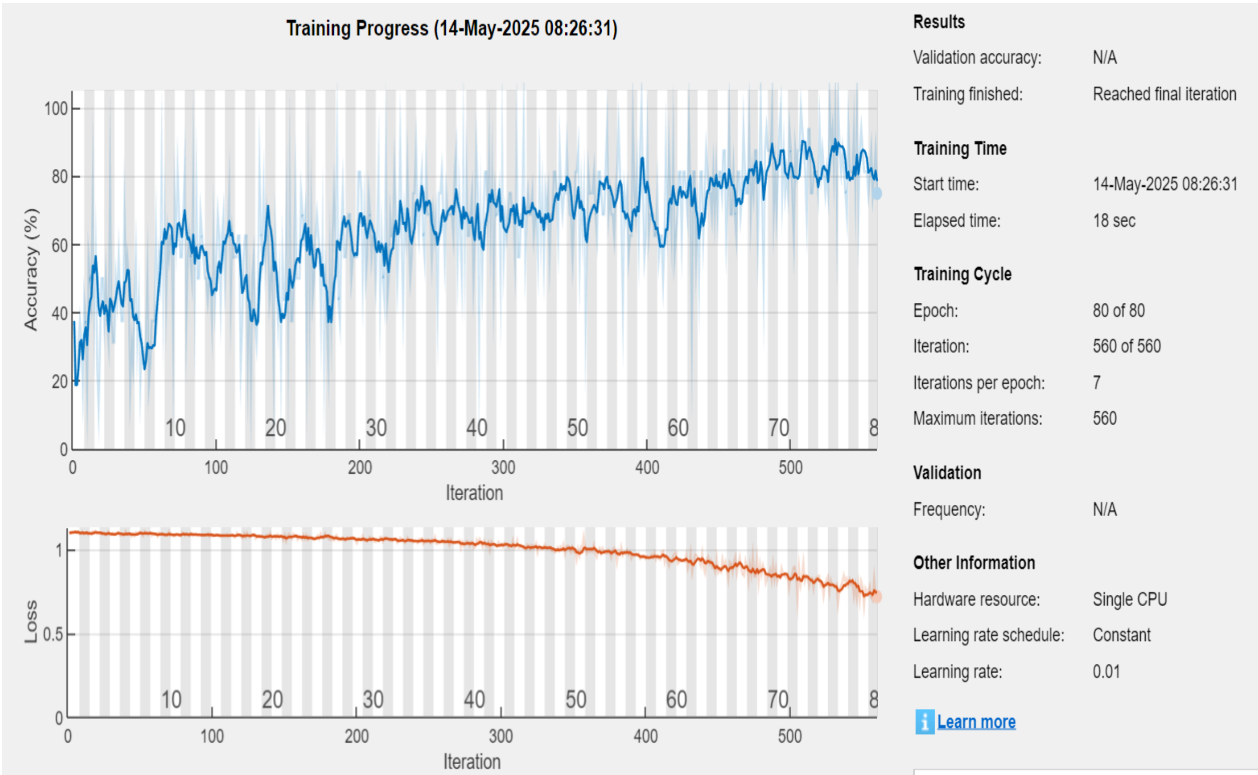

Figure 2: Training Plot of the BiLSTM

Figure 2 shows the training plot after 500 iterations showing the accuracy approaching 90%.

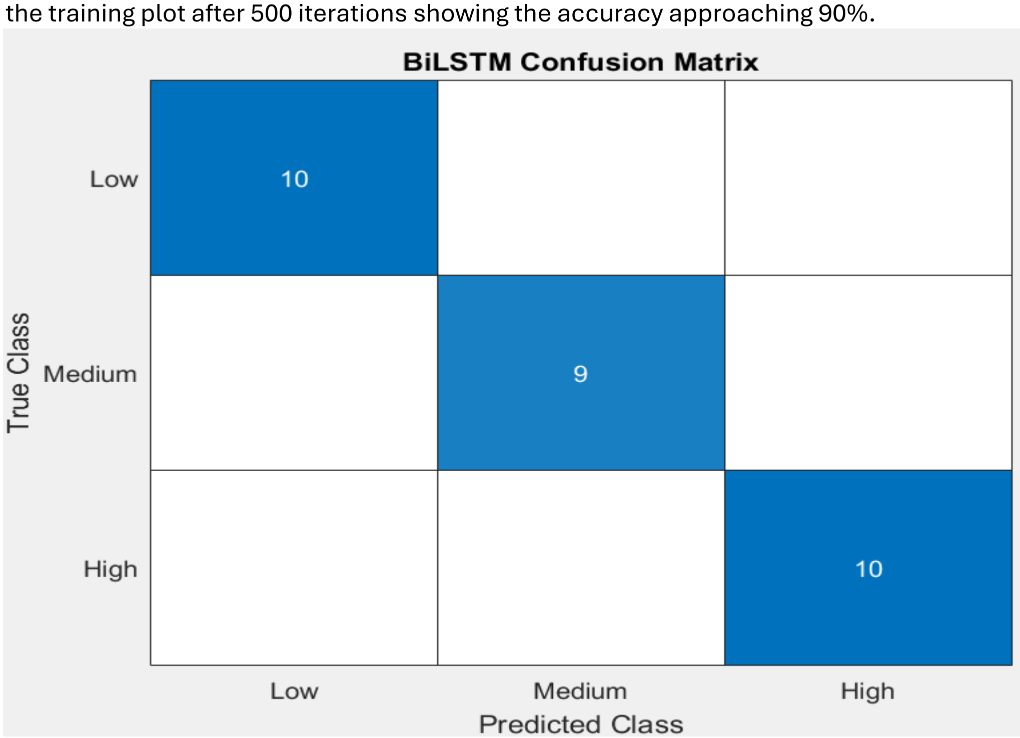

Figure 3: Confusion Plot of the BiLSTM

Table 3 shows the Confusion plot The True class, and predicated class results.

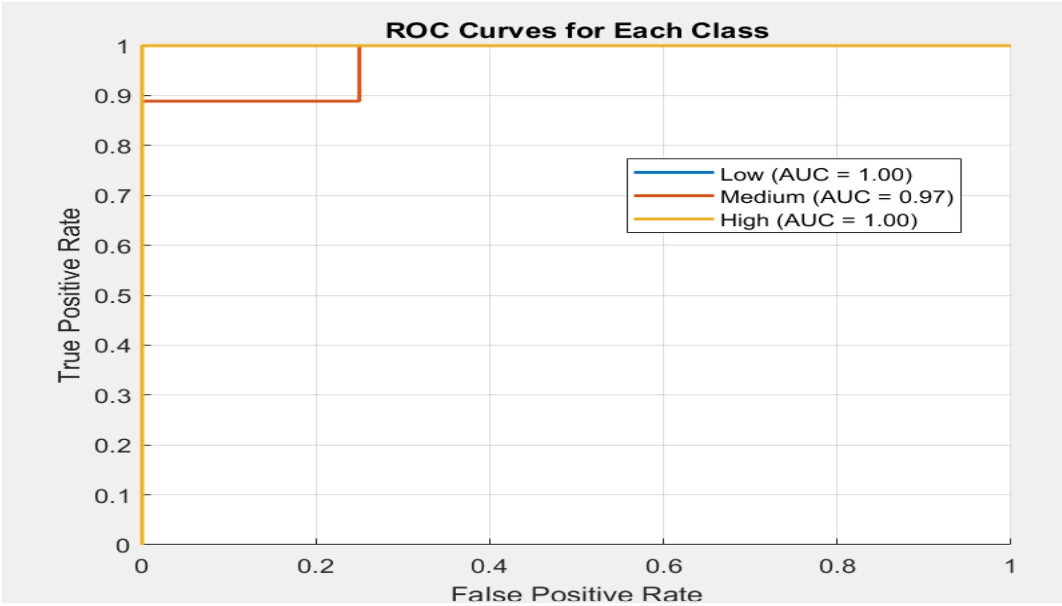

Figure 4: ROC Plot of the BiLSTM

Figure 4, presented the ROC plot, which illustrated a low AUC of 1.00, a medium AUC of 0.97, and a high AUC of 1.00. This implied that the model exhibited excellent classification performance across all categories, with near-perfect or perfect discrimination between classes. The slightly lower AUC of 0.97 in the medium category suggested a minor reduction in predictive ability, but overall, the results confirmed the robustness and reliability of the model in identifying fish health conditions across different risk levels.

The results of all the models are compared and presented in Table 2.

Table 2: Results for the proposed model

Metric	Value
Classification Accuracy	0.9655
Precision	0.9697
Recall	0.9667
F1 Score	0.96.66
Cohen's Kappa	0.9482
Average AUC	0.9947

The proposed model demonstrated outstanding performance in predicting fish mortality events, achieving a classification accuracy of 96.55%, a precision of 96.97%, and a recall of 96.67%. The resulting F1 Score of 96.66% and Cohen's Kappa of 0.9482 indicate high reliability and near-perfect agreement between predicted and actual outcomes. An average AUC of 0.9947 further validates the model's excellent ability to distinguish between elevated and non-elevated mortality cases, making it highly suitable for integration into fish management systems as a valuable tool for early warning and timely intervention.

Table 3: Comparing with benchmark paper

Metric	Proposed Model	Howarth et al. (2025)
Classification Accuracy	0.9655	0.82
Cohen's Kappa	0.9482	0.66
Average AUC	0.9947	0.91
Recall	0.9667	0.82

These results provided an in-depth analysis of the performance metrics for the proposed model for a fish management system using the BiLSTM algorithm. The results clearly indicated that the proposed model excelled across all performance metrics. With a classification accuracy of 0.9655, precision of 0.9697, recall of 0.9667, F1 score of 0.9666, Cohen's Kappa of 0.9482, and an average AUC of 0.9947, the model significantly surpassed the performance of the other models evaluated. These results highlighted the proposed model's superior ability to achieve high accuracy in mortality prediction tasks, demonstrating its effectiveness and reliability for fish population monitoring and management in aquaculture systems.

CONCLUSION

This research sought to address the shortcomings in current Fish Management Systems by developing a more advanced and reliable mortality prediction model. The main objective was to design a deep learning-based solution using the BiLSTM (Bidirectional Long Short-Term Memory) architecture to tackle the challenges often encountered in traditional fish monitoring technologies, particularly those related to temporal variability and environmental complexity.

The experimental results revealed that the proposed BiLSTM model achieved exceptional performance metrics: a classification accuracy of 0.9655, precision of 0.9697, recall of 0.9667, F1 score of 0.9666, Cohen's Kappa of 0.9482, and an average AUC of 0.9947. Compared to conventional methods, the BiLSTM model demonstrated superior accuracy and consistency in predicting fish mortality, due to its ability to learn temporal patterns and capture long-term dependencies in aquaculture data. This study marks a significant advancement in the field of fish health monitoring and management. By leveraging the BiLSTM model, the research contributes to the development of intelligent, proactive, and data-driven fish management systems. These findings offer practical value to aquaculture practitioners by enhancing early warning capabilities, improving decision-making, and supporting the sustainable growth of aquatic populations.

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