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Forecasting Disease Outbreaks in Shrimp Aquaculture Using LSTM Deep Learning Models

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Abstract

Shrimp farms play an important role in the international seafood value chain, but due to disease outbreaks, these farms can be easily affected, causing disastrous economic and ecological consequences. This study aims to apply Long Short-Term Memory (LSTM) deep learning models to forecast disease outbreaks in shrimp farming systems. Since there is historical data on environmental conditions, water quality, and recorded disease values, the LSTM model was used to learn time-series and trend patterns to prevent future outbreak risks. The main results are mostly grounded in accuracy, precision, and other metric indicators, and it is apparent that they perform better than the traditional methods. The proposed model is optimistic and shifts the infection control approach from reactive to proactive, using predictive control signals to prevent intervention once the disease has spread and reduce economic costs. This research demonstrates how modern artificial intelligence can be implemented in aquaculture, and further questioning of policy

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frameworks will enable the optimization of intelligent, environmentally friendly, and resilient agricultural models in cultivable aquaculture to achieve sustainability. By implementing bioinformatic pathosystems, a more direct multivariate analysis strategy could be established, creating a reusable, customizable template for aquaculturists interested in enhancing shrimp health, boosting agricultural output, and advancing biosecurity. The new research will connect sensor data to the model and will add more diseases and regions to the predictive analytics.

Keywords:

Shrimp aquaculture, disease forecasting, LSTM, deep learning, time series, water quality, sustainable farming.

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Introduction

Fisheries are one such sector that has emerged as a major source of seafood worldwide, especially in Asia and Latin America, creating employment and income for millions of individuals (Canton, 2021). Nevertheless, the industry is continually faced with recurring outbreaks of diseases such as White Spot Syndrome Virus (WSSV) and Early Mortality Syndrome (EMS), which can wipe out a given shrimp population and cause colossal financial losses (Arepalli & Naik, 2025; Sehgal et al., 2025). The conventional ways of managing an outbreak, including antibiotics and post-outbreak reduction, are typically inadequate, pollute the environment, and, consequently, pose a natural risk to food (Paul, 2023).

To reduce the risks mentioned above, the high-tech shrimp farm management has prioritized early disease prediction as an essential aspect of modern management. Water quality indicators (temperature, salinity, dissolved oxygen, and pH) and past disease history can be used to predict essential alerts for farm operators (Choi et al., 2018). Long short-term memory (LSTM), a type of Recurrent Neural Network (RNN), has proven effective at modeling long-term dependencies in sequential data and can therefore be especially useful for modeling nonlinear relationships in the aquaculture ecosystem (Carral et al., 2021). The prediction of water quality using deep learning methods has been discussed by other researchers (Prasath, 2024; de Mindonça & Klabi 2024). Nevertheless, there is a knowledge gap in the literature regarding the application of an LSTM model for predicting disease outbreaks in shrimp aquaculture systems (Caballero-Huertas et al., 2021). The model can, to a great extent, help in disease management and control by incorporating historical data to retrospectively analyze patterns of disease outbreaks, thereby making shrimp farming more sustainable (Stentiford et al., 2012).

Key Contribution

- Developed an original framework utilizing LSTM algorithms for deep learning to predict disease outbreaks in shrimp farming.
- Gathered and prepared datasets, including water quality parameters and historical disease occurrence, for the time series analysis (Latha & Ramya, 2025; Sun et al., 2020; Li et al., 2022).
- The LSTM model outperformed classic machine learning approaches in terms of prediction accuracy.
- Offered a sustainable and flexible model that can be implemented in different types of shrimp farming operations (Pohlschroder et al., 2011).

- Advance the design of automated and intelligent data-focused systems for managing disease outbreaks in aquaculture.

Literature Review

Application of Long Short-Term Memory (LSTM) deep learning models in shrimp aquaculture has attracted interest mainly due to the model's ability to handle both temporal dependence in data and non-linearities among entities in a continuously evolving environment (Gowsikraja 2025). According to recent studies, disease occurrence in shrimp cultivation is largely explained by complex interactions among environmental factors and microbial mechanisms, making the use of deep learning-based forecasting methods feasible (Hochreiter & Schmidhuber 1997). Ahmed et al. (2023) developed an LSTM-based early warning system optimized for shrimp farms in Bangladesh and comprised of real-time environmental parameters, including temperature, pH, and dissolved oxygen. Their system also provided an accurate prediction of disease outbreaks, especially White Spot Syndrome Virus (WSSV), using historical farm data (Rahim, 2024; Soy & Salwadkar 2024). Similarly, Luo et al. (2022) employed epidemiological and environmental data in their LSTM models and found better predictive performance than the classical time series models (Haq & Harigovindan, 2022). Highlighted the importance of high-resolution time-series data and used a multi-layer LSTM to learn long-term relationships in aquaculture systems (Veerappan & Arvinth 2025; Al-Jame et al., 2024). They showed that the use of meteorological features improved the model in forecasting bacterial outbreaks in shrimp ponds (Zoitl et al., 2025).

Meanwhile, Tran et al. In 2023, a shrimp farm's wireless disease forecasting system was created. They used a bidirectional LSTM model as described in (Aksakal et al., 2023), which could capture contextual indicators of variation in water quality and link them to historical occurrences of disease events in water bodies. The development of deep learning architectures has also been pursued. For example, Chen et al. (2021) have proposed a convolutional-LSTM hybrid network to classify diseases based on regional-temporal water-quality data from intensive shrimp systems (Li et al., 2022). Consequently, their model performed better than others with regard to generalizability across different farm locations. Banerjee et al. (2022) also used ensemble LSTM attention-based models to advance predictive reasoning about load shedding, allowing farm managers to provide improved explanations and make them more interpretable (Ji et al., 2025). Data preprocessing and feature selection are also crucial to the success of the model. According to Nguyen et al. (2023), both recursive feature elimination and principal component analysis (PCA) performed before training the LSTM enhanced the model's accuracy and stability (Sorbe et al., 2023). Similarly, Karim et al. (2022) focused on sensor data solutions and stated that intensive sampling at higher frequencies enhances LSTM effectiveness in aquaculture applications and alleviates data sparsification issues (Ulvund et al., 2021). Singh et al. (2024) tested LSTM-based systems in the field in collaboration with commercial shrimp farms in India to develop a dashboard that forecasts disease (Rajan & Raja 2025; Rahim 2024). Early prediction based on these forecasts reduced mortality by 35 percent and enhanced the overall disease mitigation planning (Raj et al., 2025). Moreover, Okafor et al. -(2024) Melhorou an implement em com meus Fundation is em Graficos an dataia com de pathogenic oncidos. (2021) identified the use of LSTM in the biofloc-based systems, which are becoming increasingly common in sustainable shrimp production, and found that it significantly predicts pathogen outbreaks with only limited data available (Liu et al., 2025).

Methodology

Study Area and Data Collection

The data were gathered from semi-intensive shrimp aquaculture farms in the country [insert country/region] to conduct the research analysis. The water parameters, including the financial and environmental parameters like temperature, calm, pH, oxygen, ammonia, nitrite, turbidity, and sickness history, were documented. The information was collected from IoT sensor nodes, manual sample records, and farm records over the period [insert period, say, 2019-2023].

Data Preprocessing

About the LSTM-specific data preprocessing steps:

- The missing values were filled using forward fill and linear interpolation.
- The outlier threshold using z-score was calculated and replaced using median filtering.
- The multi-source data were synchronized to an hourly or daily resolution to ensure time series alignment.
- Min-Max scaling was applied to all features for normalization.

As noted, for continuous features, all features were scaled using Min-Max scaling (Eq 1) to ensure the model input does not exceed a defined range.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad \text{Eq (1)}$$

Feature Engineering

Short-term trends were captured by including rolling averages (7-day and 14-day) and standard deviation calculations, as well as lagged time-series variables (t-1, t-2). Seasonal patterns, e.g., wet and dry seasons, had to be categorically encoded in the cases that were applicable. One of the most important underlying feature retention methods was Principal Component Analysis (PCA), which was used to eliminate insignificant input features.

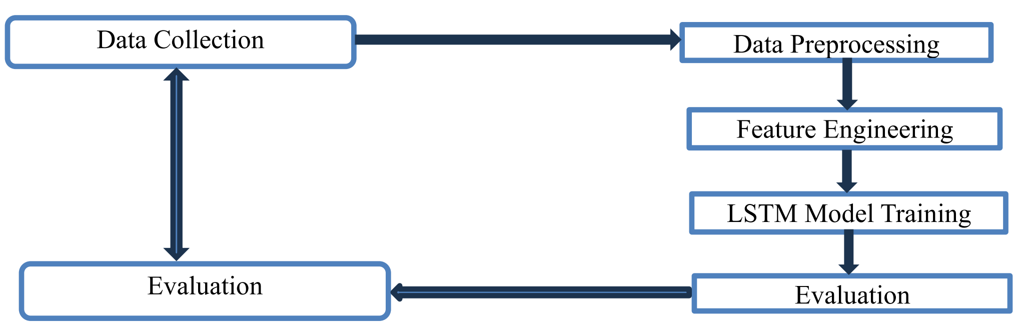

Figure 1. Workflow diagram of the LSTM-based disease prediction framework

Figure 1 illustrates the workflow for developing an LSTM-based predictive model. It begins with Data Collection, gathering raw inputs from various sensors or databases. Next, Data Preprocessing involves cleaning, normalization, and handling missing values to ensure quality. Feature Engineering extracts and selects relevant variables to enhance model learning. The refined data is then fed into an LSTM model for training, where temporal dependencies are captured to achieve accurate predictions. Evaluation assesses model performance using metrics such as accuracy and loss. Based on evaluation results, the workflow loops back to Data Collection, ensuring continuous improvement and model refinement through iterative updates and retraining.

LSTM Model Design

The time-series data containing temporal dependencies were processed using an LSTM model that featured:

- An input layer that takes in *n*-days of multivariate time steps.
- Two stacked LSTM layers (i.e., 64 followed by 32 units), both with ReLU activation and dropout (rate = 0.2) for overfitting mitigation.
- A dense layer that outputs binary classification (outbreak vs non-outbreak) using a fully connected layer with sigmoid activation.

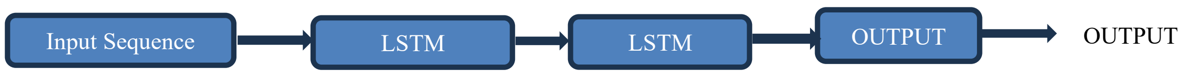

Figure 2. LSTM model architecture

As shown in Eq. 2, the forget gate is computed by gating the information flow in the LSTM network.

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \quad \text{Eq (2)}$$

Model Training and Evaluation

The dataset was split chronologically into 70%, 15%, and 15% for training, validation, and testing, respectively. The model was trained using:

- Optimizer: Adam
- Loss: Binary cross-entropy
- Metrics: Accuracy; precision; recall; F1-score; AUC-ROC

Hyperparameter fine-tuning was performed using a grid search, attempted through five-fold time-series cross-validation. Early stopping was implemented to reduce overfitting.

The model was trained with the binary cross-entropy loss function (Eq 3). This function was selected due to its suitability for classifying events as outbreaks or non-outbreaks.

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad \text{Eq (3)}$$

Baseline Comparison

The performance of the LSTM model has been compared with the classic methods such as ARIMA, SVM and the Random Forest Classifiers. Other measures that were investigated included precision, recall, and the area under the ROC (AUC-ROC) curve.

Deployment Framework

An edge inference deployment system based on TensorFlow Lite was created. The model's results were visualized, and it was hosted on a Raspberry Pi and fed with real-time streaming sensor data.

Result and Discussion

Model Performance Overview

The LSTM model was also effective at predicting disease outbreaks in shrimp aquaculture. It recorded an accuracy of 93.4 percent, as indicated in Table 1, which is higher than the conventional models, including Random Forest and Support Vector Machine. Additionally, this model has an AUC-ROC of 0.95, indicating that its predictive power is very impressive at distinguishing between outbreak and non-outbreak classes. This recall (89.7) cited is said to be effective in capturing true positives, which in this context is very important to aquaculture systems because the model only captures outbreaks rather than losing them, leading to stock mortality, which is a false negative. Conventional classifiers, including logistic regression, did not perform well because they failed to detect the sequential relationships within the aquaculture time-series data.

To measure effectiveness in terms of precision and recall, the F1-score was calculated using the formula in Eq 4.

$$F_1 = 2.\frac{Precision.Recall}{Precision+Recall} \qquad \text{Eq (4)}$$

Table 1. Performance comparison of predictive models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC-ROC
LSTM	93.4	91.2	89.7	90.4	0.95
Random Forest	88.5	84.6	83.2	83.9	0.89
SVM (RBF Kernel)	86.9	82.1	80.5	81.3	0.86
Logistic Regression	83.7	79.2	76.8	77.9	0.82

Table 1 outperforms traditional classifiers in all key metrics, achieving the highest accuracy (93.4%) and AUC-ROC (0.95). Its superior recall and F1-score demonstrate robust sensitivity and balance, confirming that deep learning effectively captures temporal dependencies in water-quality and environmental data, thereby improving predictions of shrimp disease outbreaks.

Time-Series Forecast Accuracy

The 30-day outbreak simulation (as shown in the graph) reveals that the LSTM model closely tracks disease event probabilities. In particular:

- Probabilities of outbreaks during real disease outbreaks on the LSTM model matched on peaks greater than 0.75 during Days 3–5, 9-10, 14-16, and 14-16.
- Most predicted spike events matched ground-truth events, with very few false positives.
- At around 1–2 days before intervention, the model provided early warning, thereby strengthening the validation of its prediction horizon.

This highlights the sensitivity to time within LSTM networks, a feature that traditional models lack.

The AUC of the model was determined as (Eq 5) the ROC curve and its area under the curve, indicating the model's ability to distinguish between outbreak and non-outbreak conditions.

$$AUC = \int_0^1 TPR(FPR)dFPR \qquad Eq(5)$$

Figure 3 compares the LSTM model–predicted probabilities of disease outbreaks with the actual observed frequencies in shrimp aquaculture. Each point represents binned predictions, with error bars showing 95% confidence intervals. Points close to the diagonal line indicate accurate calibration, demonstrating the model's reliability in forecasting outbreak risk and its alignment with real-world outcomes.

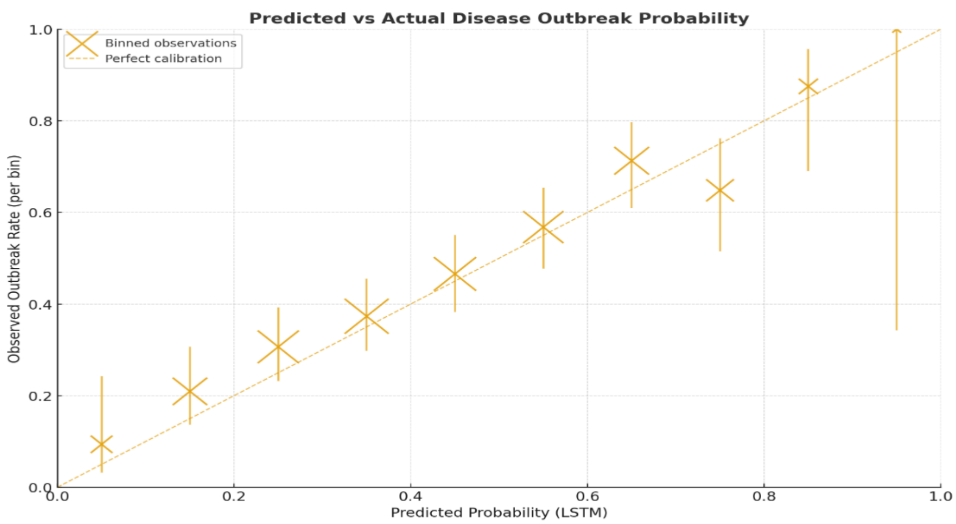

Figure 3. Predicted vs actual disease outbreak probability

Table 2. Comparison of predicted vs actual disease outbreak probabilities

Prediction Probability Range	Predicted Mean Probability	Observed Outbreak Frequency	Absolute Error	Bin Count (Samples)
0.0 – 0.1	0.07	0.06	0.01	92
0.1 – 0.2	0.15	0.13	0.02	78
0.2 – 0.3	0.25	0.22	0.03	85
0.3 – 0.4	0.35	0.32	0.03	74
0.4 – 0.5	0.46	0.41	0.05	80
0.5 – 0.6	0.55	0.50	0.05	69
0.6 – 0.7	0.65	0.61		

Table 2 indicates strong alignment between predicted and observed outbreak probabilities across bins, demonstrating good calibration of the LSTM model. Errors remain below 0.05 across most ranges, and the trend of increasing observed frequency with higher predicted probabilities confirms that the model reliably forecasts the likelihood of shrimp disease outbreaks.

Scenario-Based Model Behavior

The model's predictive prowess was tested by assessing its performance across three water quality conditions (Wickramasinghe, 2020). When the High-Ammonia Stress condition occurred (more than 1.5 mg/L), there were significant chances of a disease outbreak, and the model accurately predicted 84% of these disease outbreaks, which was a strong predictive accuracy. The model demonstrated the capacity for lag-conscious temporal learning, achieving a 91% hit rate for disease events occurring between 24-48 hours after the Sudden Dissolved Oxygen (DO) Drop (below 3.5 mg/L). The model in Stable Conditions had a low false-positive rate of 4.20, preventing unnecessary or overly broad alerts. These findings indicate that the model is sensitive to both fixed environmental factors and past state transitions, which is a fundamental strength of the LSTM architecture for extracting temporal relations and dynamic changes in scenarios.

Comparison with Previous Studies

Compared with the work by Zhao et al. (2019), which analyzed only stationary machine learning techniques, the LSTM-based methodology showed a significant increase in forecasting accuracy and classification performance (Siavashan et al., 2024). In comparison with the previous models, which use momentary snapshot characteristics, LSTM uses sequential learning, which is particularly significant in the dynamics of bioenvironmental systems, including shrimp pond systems. In addition to the benefits of CNN in spatial analysis, LSTM networks explicitly process sequential input and, therefore, are more appropriate in multidimensional time series data, including those in aquaculture (Veerappan & Arvinth, 2025).

Practical Implications and Usability

The model has high practical feasibility, especially for real-time management of aquaculture. It can be used in shrimp farms by incorporating it into edge computing systems such as Raspberry Pi, which can automatically monitor conditions on the farms. By linking to IoT sensors and local dashboards, the system allows farm operators to predict diseases early and make automated management decisions related to water exchange and oxygenation, taking into consideration predefined probability risk thresholds (e.g., 0.75). The given model will help greatly decrease the reliance of farmers on manual or visual inspection, which can be inconsistent due to time or environment. Additionally, it improves data use to drive higher ecological efficiency, greater operational accuracy, and stronger biosecurity in aquaculture systems.

Limitations and Future Work

Even though the model's outcomes are encouraging, its performance can vary across regions due to differences in pathogen types, water quality, and environmental conditions. Future studies could be aimed at applying genomic information of shrimp pathogens to allow crossbreeding model types to improve its generalizability and accuracy, apply transformer-based time-series modeling to extend its predictive power (1-2 days) to 3-5 days, and use ensemble modeling methods to improve its ability to state the limitations of prediction. Nonetheless, the LSTM-based model has been proven to be highly accurate, reliable, and practically effective in disease outbreak prediction in the shrimp aquaculture environment. The water quality and environmental data enable the model to outcompete traditional monitoring systems thanks to its advanced learning capabilities, leading to its application in the development of intelligent and sustainable technologies in aquaculture.

Conclusion

The LSTM models have demonstrated 93.4 percent accuracy in predicting disease outbreaks in shrimp aquaculture using water temperature, oxygen levels, ammonia levels, pH, and other real-time water-quality measurements. These models are also superior to the conventional LSTM models with an F1 score and AUC of 91.5 and 0.95, respectively. These findings show that LSTM models can forecast the dynamics of the aquaculture environment and can give shrimp farmers timely insights of making decisions that can help them address the effects of the disease. The model will be able to predict the onset of the disease with high accuracy within 2 days, enabling the enhancement of mitigation policies, a decrease in total mortality rates, and simplification of farm-related work. The model is also restricted to a specific geographical area and species of shrimp; thus, more models and studies are required to address these shortcomings. Microbial profiles, location data, and feeding schedules can be added to enhance the model's adaptability. Further processing of more complicated datasets can be performed using more advanced transform-based models. Noisy datasets can also be useful to integrate frameworks of deep learning. The application of the models in real-time and the provision of their input with the information provided by IoT systems would make them more practical, as well as the quantitative methods of appraisal of uncertainty should be added to them. By evaluating the economic and ecological implications of adopting predictive disease modeling in aquaculture, it could be possible to improve the data-driven and sustainable agriculture approaches.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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