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LGA-NET: A LSTM-GRU-ATTENTION LAYER HYBRID NETWORK FOR WATER QUALITY ASSESSMENT IN SMART AND SUSTAINABLE AQUACULTURE

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Abstract

Water quality management in aquaculture is important as it directly impacts aquatic animals and plant's health, growth, and productivity. Management of water conditions at their optimum promotes innovative and sustainable aquaculture production at maximum yield. Traditional approaches to water quality measurement are by intermittent sampling, which only gives a snapshot of environmental conditions at a particular moment. The approaches are slow, labor-consuming, and incapable of feeding back real-time data on key parameters like pH, dissolved oxygen, and temperature. As a result, critical water quality issues may go undetected until they reach harmful levels, leading to significant losses in aquaculture systems. This study explores using deep learning models to improve the accuracy and efficiency of water quality forecasting. Leveraging large datasets and advanced neural network architectures, the proposed LGA-Net: A LSTM-GRU-Attention Layer Hybrid Network for Water Quality Assessment in Smart and Sustainable Aquaculture aims to provide real-time, data-driven intelligence for proactive decision-making in aquaculture management. The model is educated on past water quality data and identifies complex patterns and relationships between parameters to produce accurate forecasts. In contrast to conventional monitoring, real-time forecasting based on deep learning avoids sudden environmental shifts, allowing real-time response and risk minimization. The findings of this study highlight the capability of deep learning to transform the process of innovative and sustainable water quality management. With the integration of artificial intelligence into aquaculture systems, experts can optimize environmental conditions, reduce the need for reactive measures, and optimize overall sustainability. This study highlights the ability of technological innovation to ensure robust and efficient aquaculture operations, contributing to food security globally and smart and sustainable fisheries management.

1. Introduction

Aquaculture is the cultivation of aquatic living things like fish, shellfish, and aquacrops and constitutes a vital part of the world's food security and economy. There has never been such high demand for smart and sustainable productive sources of food owing to the prolonged increase of

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the world's population. Aquaculture complements the natural supply of seafood and offers livelihood opportunities to millions of individuals across the globe. Optimal water quality is of prime importance to the health and development of aquatic life, and the most important parameters like pH, dissolved oxygen content, temperature, and nutrients must be carefully monitored. The conventional practice of water quality evaluation is primarily through manual sampling and time-consuming operations that slow responses to crucial changes and cause substantial financial losses through fish sickness or lost yields. However, recent machine and profound learning breakthroughs are changing how smart and sustainable aquaculture businesses deal with water quality. With large amounts of data from fish farms, the technologies can forecast key water quality parameters with higher accuracy than current practice, enabling aquaculturists to make quality decisions in real-time and simplifying the overall efficiency of their operations. The incorporation of AI-based solutions enhances fish health, enhances production efficiency, and encourages resource conservation and smart and sustainable practices in the industry. With continued research on this front, the potential of building resilient and smart and sustainable aquaculture practices is made increasingly viable, thus allowing this important industry to be resilient in the face of future adversity while meeting world food demands.

This research investigates the application of deep learning models to enhance the precision and efficacy of water quality predictions. The proposed LGA-Net: A LSTM-GRU-Attention Layer Hybrid Network for Water Quality Assessment in Smart and Sustainable Aquaculture utilises extensive datasets and sophisticated neural network architectures to deliver real-time, data-driven insights for proactive aquaculture management decisions. The algorithm is trained on historical water quality data and discerns intricate patterns and correlations among parameters to generate precise projections. Unlike traditional monitoring, real-time forecasting utilising deep learning circumvents abrupt environmental changes, facilitating immediate response and risk reduction. This study's findings underscore deep learning's potential to revolutionise innovative and sustainable water quality management.

2. Literature Survey

The research community presented diverse methodologies for water quality assessments in the field of aquaculture. Wu-Chih Hu et al. (2022) highlight the importance of different sensors and computer vision technologies in improving the accuracy of fish feeding monitoring and control. Sensors are used to identify surface agitation due to fish feeding activity, while computer vision systems utilize sophisticated image processing and machine learning techniques to examine underwater feed. This integration of technology contributes to a more efficient and sustainable aquaculture system by minimizing feed wastage, optimizing feeding schedules, and improving overall productivity. Yangde Li et al. (2022) propose an advanced K-GRU prediction model that combines deep learning techniques with an improved K-means clustering approach. This model shows better accuracy and reliability in predicting water quality parameters than traditional predictive models, and its potential for the improvement of aquaculture water management. K. P. Rasheed Abdul Haq et al. (2022) aim to enhance water quality prediction (WQP) in aquaculture by developing hybrid deep learning models that integrate Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). These hybrid models utilize the ability of CNN for efficient feature extraction and LSTM and GRU for identifying long-term dependencies in time-series data. The main goal is to improve the accuracy of WQP, minimize computational time, and maintain the stability and sustainability of aquaculture systems. By predicting key water quality parameters like salinity, pH, dissolved oxygen, and temperature, the intended models alleviate the negative impacts of water quality fluctuations on aquatic life. This allows for more profitable and sustainable aquaculture management through early interventions and optimal environmental control.

Miguel Chicchon et al. (2023) focus on enhancing water quality prediction (WQP) in aquaculture by developing hybrid deep learning models that integrate Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). These hybrid models utilize the feature extraction ability of CNN with the power of LSTM and GRU in identifying long-term dependencies in time-series data. The major goal is to enhance the accuracy of WQP, minimize computational complexity, and guarantee the stability and sustainability of aquaculture systems. Through the forecasting of key water quality parameters like salinity, pH, dissolved oxygen, and temperature, the projected models seek to counteract the negative impacts of water quality fluctuations on aquatic life. This foresight-based technique leads to more sustainable aquaculture practices through optimized resource consumption and enhanced profitability.

Wu-Chih Hu et al. (2024) propose the development and implementation of a real-time artificial intelligence of things (AIoT)-based water quality monitoring and prediction system for smart fish farming. The system utilizes a Simple Recurrent Unit (SRU) model to forecast water quality parameters, enabling fish farmers to collect and analyze sensor data continuously. A 24-hour water quality sample tank is incorporated to correct sensor errors, ensuring data reliability. The gathered information is sent to a cloud platform, where there is continuous monitoring and predictive water quality analysis. Experimental outcomes confirm the system's efficacy in accurately predicting water conditions. Additionally, the study highlights the impact of climate change on aquaculture and the increasing global demand for aquatic species such as fish, shrimp, and shellfish. While traditional aquaculture management methods are labor-intensive and time-consuming, advancements in AI and IoT technologies have transformed conventional aquaculture into smart aquaculture. But even with these technological developments, existing smart aquaculture systems are not enough to comprehensively meet the increasing global food deficit, which means there is a necessity for more innovation and optimization.

Charvi Kusuma et al. (2023) analyze the architecture of an automatic monitoring system designed to improve aquaculture practice in India. The system utilizes artificial intelligence to detect dead fish on the surface of the water, which is an indicator of probable imbalances in the pond's ecosystem. Through the application of the YOLOv5 deep learning model, the system attains a real-time dead fish detection accuracy of 88%. Through the provision of real-time alerts to the farmers, the system enables taking early measures to prevent negative impacts on the quality of water and the well-being of the fish in general. The study also examines the importance of the fish farming industry in the Indian economy and the use of deep learning for the development of smart aquaculture practices. Despite the accelerated growth in the industry for fish farming, its technology remains underdeveloped. This research aims to enhance the sustainability and performance of fish cultivation through the use of AI-object detection, which helps farmers easily detect and address issues quickly, hence higher productivity and lower losses.

Vinoth Kumar et al. (2023) highlight the environmental challenges facing inland fisheries, including water pollution and habitat loss, which threaten the sustainability of aquatic ecosystems. Industrial aquaculture has largely influenced water resources, habitat structures, and aquatic diversity, resulting in issues such as the reduction of indigenous wild fish stocks and the spread of disease and parasites. Due to these problems, ongoing monitoring of water quality is crucial to achieving ecological equilibrium and guaranteeing sustainable aquaculture. This study reviews existing research on water quality prediction and proposes a novel smart aquaculture system utilizing a Machine Intelligence (SAS-MI) model. The suggested model combines a Deep Convolutional Neural Network (D-CNN) and k-means clustering to improve the accuracy of water quality prediction. Through the use of deep learning methods, the SAS-MI model enhances predictive performance by automating feature extraction. The model is assessed in the research by comparing it with current water quality prediction models. Experimental findings prove that the SAS-MI model performs better in prediction accuracy, F1-score, and Mean Squared Error (MSE), reflecting its applicability in real-world smart aquaculture management.

Haijing Qin et al. (2023) discuss how machine learning enhances the development of accurate predictive models of environmental elements in aquaculture. The growing implementation of water quality monitoring technologies has become pivotal for tracking aquatic environments. But these sensors are usually prone to errors caused by the interference from the surrounding environmental conditions, leading to data loss and outliers. In response to these challenges, the creation of accurate water quality forecasting models and predictive frameworks is important for fostering sustainable aquaculture practices. The study categorizes water quality prediction approaches into two primary groups, mechanistic modeling and data-driven non-mechanistic models. Conventional statistical forecasting methods, including Multiple Linear Regression and Auto-Regressive Integrated Moving Average, tend to be intricate and heavily reliant on parameter choices. Conversely, recent developments in shallow machine learning and deep learning methods have facilitated more accurate and efficient aquaculture water quality prediction models. This paper discusses major methodologies and common practices in using machine learning models to predict environmental factors in aquaculture. It also discusses current challenges in model design and highlights the necessity of speeding up the integration of water environment monitoring with predictive technologies to support future aquaculture management.

Vinh Tran-Quang et al. (2021) present an enhanced Long Short-Term Memory (LSTM) deep learning model for predicting environmental conditions in aquaculture. The study focuses on improving the accuracy of standard LSTM models by incorporating key environmental parameters

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relevant to lobster farming. Real-world environmental data from the Xuan Dai Bay monitoring center in Phu Yen province, Vietnam, were employed to train and evaluate the proposed model. The research compares the predictive performance of the enhanced LSTM model with that of traditional Recurrent Neural Network (RNN) models. The outcomes illustrate that the enhanced LSTM model clearly outperforms RNN-based methods in predicting aquatic environmental parameter changes. The results highlight the significance of real-time identification of water quality fluctuations in aquaculture since variations in such can have critical implications for marine organisms and cause enormous economic losses for aquaculture farmers. The research underscores the advantages of deep learning to optimize environmental monitoring and promote sustainable aquaculture operations.

Tien-Sheng Lin et al.(2021) emphasize the development and deployment of a smart monitoring system for shrimp aquaculture that leverages convolutional neural networks and deep learning techniques. This system focuses on the fixed environmental factors of shrimp farms and utilizes them to manage dynamic variables such as feeding, growth, movement, and emergency alerts. Through the integration of edge computing, the described system enhances productivity on farms while also mitigating the risk of sudden devastation caused by unknown occurrences. The study identifies the optimal approach for integrating edge computing into automated shrimp farming systems. It considers various environmental factors, including static, dynamic, and combined data, such as temperature, dissolved oxygen, pH, salinity, and other key water quality indicators. The static information is sent to the cloud for CNN classification in order to achieve big data analysis and machine learning, while dynamic information is used to monitor the growth rate of shrimp larvae in order to improve the efficiency of shrimp farming.

Tianan Deng et al. (2021) highlight that over the past three decades, harmful algal blooms (HABs) have increasingly impacted coastal waters worldwide, including in Hong Kong. The rising frequency of HABs has caused significant harm, resulting in millions of dollars in losses for the marine aquaculture industry and the surrounding water environment. Tolo Harbour, in particular, has been one of the most severely affected areas, accounting for over 30% of the region's HAB incidents. To predict and mitigate future HAB-related disasters, experts are employing Machine Learning (ML) techniques to model and forecast water quality issues. This study compares and applies two distinct ML approaches, Artificial Neural Networks (ANN) and Support Vector Machines (SVM), integrating various hybrid learning algorithms to enhance the simulations. Based on these analyses, the authors describe the methodology used to assess water quality, manage the situation, and support decision-making processes.

Sohom Sen et al. (2023) describe the characteristics of an IoT-based dataset used to train and validate AI models for water quality monitoring. The dataset includes measurements from sensors that track variables such as solids, chloramines, sulfate, pH, hardness, conductivity, trihalomethanes, organic carbon, turbidity, and portability. The dataset is stored in a CSV file format, with portability as the target variable, and the other nine variables serving as predictors. The dataset has dimensions of 3276 x 10, representing 3276 samples and 10 variables. Before

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applying machine learning (ML) models, the data underwent preprocessing. First, null values were identified and removed. Then, outliers were detected and eliminated using the Interquartile Range (IQR) method. After addressing the missing and invalid data, the remaining dataset was divided into training and evaluation sets, with 15% of the data allocated for testing. All features were standardized using a scaling technique to ensure they fell within a comparable range. A flowchart of the suggested methodology displays the distribution of the nine predictor variables after preprocessing. Interestingly, an examination of the turbidity variable indicated a dramatic change in its distribution after preprocessing.

Elias Eze et al. (2023), with emphasis on hybrid deep neural networks to predict multivariate water quality in aquaculture systems. The research underscores the need to monitor important water quality parameters, enabling the early detection of possible problems and allowing decision-makers to intervene and prevent issues before they escalate, thereby enhancing aquaculture industry water quality management. The researchers developed a novel multivariate water quality forecasting model using a hybrid deep learning approach, combining the Exact Mode Decomposition (EEMD) method, multivariate linear regression (MLR), and long short-term memory (LSTM) neural network regression techniques. The resulting model, EEMD-MLR-LSTM NN, utilizes multivariate time-series data from water quality sensors. The study was conducted at Loch Duart, a salmon offshore aquaculture farm in Scourie, northwest Scotland. To demonstrate the effectiveness of this hybrid forecasting model, the researchers compared phytoplankton data and measured water quality parameters from the aquaculture farm. The results suggest that this new model can significantly enhance the ability of aquaculture businesses to manage water quality effectively.

Md. Mamunur Rashid et al. (2021) emphasize the many fish farming issues, such as water contamination, temperature fluctuations, feed management, space, and high operational expenses. Biofloc technology in aquaculture provides a remedy by converting conventional methods into a sophisticated system that recycles uneaten feed and produces microbial protein as a by-product. This paper seeks to present an IoT-based solution designed specifically for aquaculture that optimizes productivity and efficiency. The system uses sensors to gather data, which a machine-learning model processes to aid decision-making. Artificial intelligence is employed to send real-time alerts to users. The team has successfully implemented and tested the proposed approach, verifying its effectiveness and achieving promising results.

Trong-Nghia Nguyen et al. (2022) highlight the important contribution of deep learning and machine learning in driving intelligence and automation in different industries, including aquaculture. In recent times, the use of learning algorithms in aquaculture has created new avenues for digitalization of the industry. Water quality management, which is critical to the health of aquatic life, is one such area of interest. This research suggests a holistic deep learning-based TabNet model for water quality prediction. Using pre-dominant machine learning and deep learning algorithms, the model is applying key markers to predict counts of water cells in new fish farming counting approaches. The paper also discusses deep learning's uses in fish farming and

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the effective results it has the potential to produce. Experiments with internal data proved this to be effective, pointing towards the cost reduction, time-saving, and streamlining of the process of fish farming that can be achieved by using AI. Jing Su and Jiahong Chen (2020) highlight the significant impact of water quality on the success or failure of fish farming. Currently, fish farming heavily relies on the expertise of workers, which is insufficient for effectively controlling water quality. The current monitoring systems for hydroponic agriculture primarily monitor water quality but cannot analyze or interpret the data in-depth. Also, there has been minimal research on the forecast of future water quality. To address these challenges, the authors propose a system founded on deep learning for aquaculture water quality management. With sophisticated AI and big data technologies, the system displays water quality data, forecasts future developments, detects probable problems, and issues warnings. Through this process, fish farmers can manage their activities more effectively and make informed decisions, enhancing their productivity and stock health.

Al-Akhir Nayan et al. (2021) highlight the need for fish farmers to determine the causes of fish diseases and prevent them from occurring to prevent outbreaks, which can cause substantial economic losses and adversely affect the economy. Fish diseases are usually caused by viruses and bacteria, which can change the pH levels of the water. Chemicals like dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total suspended solids (TSS), total dissolved solids (TDS), electrical conductivity (EC), and compounds like PO_4^{3-}, NO_3^-, and NH_3-N are toxic to fish health if they are in the water. Natural phenomena such as photosynthesis, respiration, and decomposition also contribute to changes in water quality that impact fish health. This paper suggests applying sophisticated machine learning algorithms and methods to identify and forecast water quality downturns based on the latest developments. This would allow for proactive interventions to avoid fish disease. The experiment results demonstrate that assessing water quality through these methods can effectively predict potential fish health issues using real-world datasets.

Andres Felipe Zambrano et al. (2021) emphasize the importance of monitoring water quality factors such as dissolved oxygen, pH levels, and temperature in fish farming to ensure optimal conditions for fish growth. Traditionally, machine learning (ML) methods have been applied to real-time, remote-sensing data gathered by advanced devices. This setup allows for accurate predictions and enables fish farmers to make informed decisions. However, not all farmers have access to these high-tech devices; many still rely on manual tools to measure these factors, which limits the amount of data they can collect and process. This study explores the effectiveness of three ML techniques—random forests, multivariate linear regression, and artificial neural networks—in scenarios with limited data. Using water quality factors commonly measured by fish farmers, the authors propose two main approaches: 1) predicting unknown water quality factors based on those already measured and 2) making predictions with minimal data. The results show that random forests, even with just two daily measurements, can accurately predict key water quality variables such as dissolved oxygen, pond temperature, pH, ammonia, and ammonium. Furthermore, the authors demonstrate that these prediction models can be integrated into a mobilebased information system that can run on an affordable smartphone, making it accessible to fish farmers in resource-constrained settings.

Labonnah Farzana Rahman et al. (2021) highlight the significant role of the fishing industry in enhancing domestic protein production, especially in Malaysia, where shifts in global weather patterns continue to impact aquaculture and sea fish farming. Despite the importance of these systems, machine learning (ML) has yet to be extensively applied in the study of Malaysian water systems. However, integrating ML algorithms with feature importance analysis offers an opportunity to improve prediction accuracy and uncover valuable insights into fish production. This study focuses on predicting the output of sea fish and aquaculture using ML. Based on their importance scores, the authors select key climatic variables for each ML model—linear regression, gradient boosting, and random forest. Data on climatic variables and fish production from 2000 to 2019 were used to train and test the models. To enhance prediction performance, the study employs voting regression, an ensemble method that combines the results of the three ML models. The results indicate that ensemble ML model performs better than individual models with R^2 values of 0.75, 0.81, and 0.55 for marine, freshwater, and brackish fish production. The results indicate that ensemble ML methods make more accurate predictions of fish production in Malaysia compared to single-model methods, enabling improved understanding and management of the nation's fish farming sector.

Ming Sun et al. (2020) note that hydroponics is an intricate interactive process that requires various factors such as animal, human, and capital investments that all play essential roles in managing water resources. The system depends on diverse, nonlinear environmental factors, and controlling the process is tricky due to their complex natures. The conventional artificial intelligence (AI) approach has been unable to satisfy the needs of such systems in real life since the models tend not to pick up the significant features from the data. Deep learning, a branch of AI, has been discussed in academic and industrial circles because it can automatically discover important features from unprocessed data. As a result, its application to hydroponics is expected to yield significant improvements. Numerous studies have demonstrated the potential of deep learning to detect, classify, count, and predict outcomes across various domains. The paper discusses the application of deep learning in aquaculture, particularly for sea products, and structures the research into major categories. These are fish counting, behavior monitoring, and defect detection in fish fillets. The paper provides examples of existing work in these categories, showing the real-life applications and the increasing influence of deep learning in improving aquaculture practices.

Scientists utilize deep learning techniques to detect and study shrimp diseases, assess freshness, sort pearls, and count scallops. They also identify coral species, monitor jellyfish populations, track cold-water coral polyp activity, classify aquatic macroinvertebrates, and categorize phytoplankton. Additionally, research efforts focus on predicting red tide biomass trends, estimating oxygen levels, forecasting chlorophyll-a content, and modeling temperature fluctuations. In fish farming, deep learning is crucial in monitoring aquaculture environments using sea-based floating platforms, navigating obstacle-filled water settings, and even enabling

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virtual fish-grab simulations. Our findings indicate that deep learning techniques markedly improve precision and productivity over conventional approaches in most investigations. In addition, we introduce the strengths and weaknesses of deep learning in aquaculture, pointing out essential difficulties and possible solutions for future improvements.

3. LGA-Net: A LSTM-GRU-Attention Layer Hybrid Network

The Proposed LGA-Net Framework integrates multiple components to process time-series water quality data efficiently and accurately. It begins with a User Interface (UI) or Graphical User Interface (GUI) that allows users to input water quality parameters and retrieve predictions based on historical and real-time data. The data from the GUI is transmitted to the Backend Web Server, which handles API requests and data points for further processing. The backend web server is an intermediary, enabling secure communication between the UI and the core prediction model through API Endpoints and Data Points. Initially, the raw data undergoes preprocessing, including cleaning to handle missing values and outliers, normalization to standardize feature scales, and data splitting into training, validation, and test sets. The core prediction model is a Hybrid LSTM-GRU-Attention Network (**LGA-Net)**, combining Long Short-Term Memory (LSTM) for capturing long-term dependencies, Gated Recurrent Units (GRU) for extracting relevant sequential patterns efficiently, and an Attention Mechanism that enhances interpretability by assigning importance to critical time steps. The LGA-Net model processes time-series water quality data using deep learning techniques. **Figure 1** illustrates the water quality analysis framework, which incorporates GUI layers and the LGA-Net framework for Smart and Sustainable Aquaculture.

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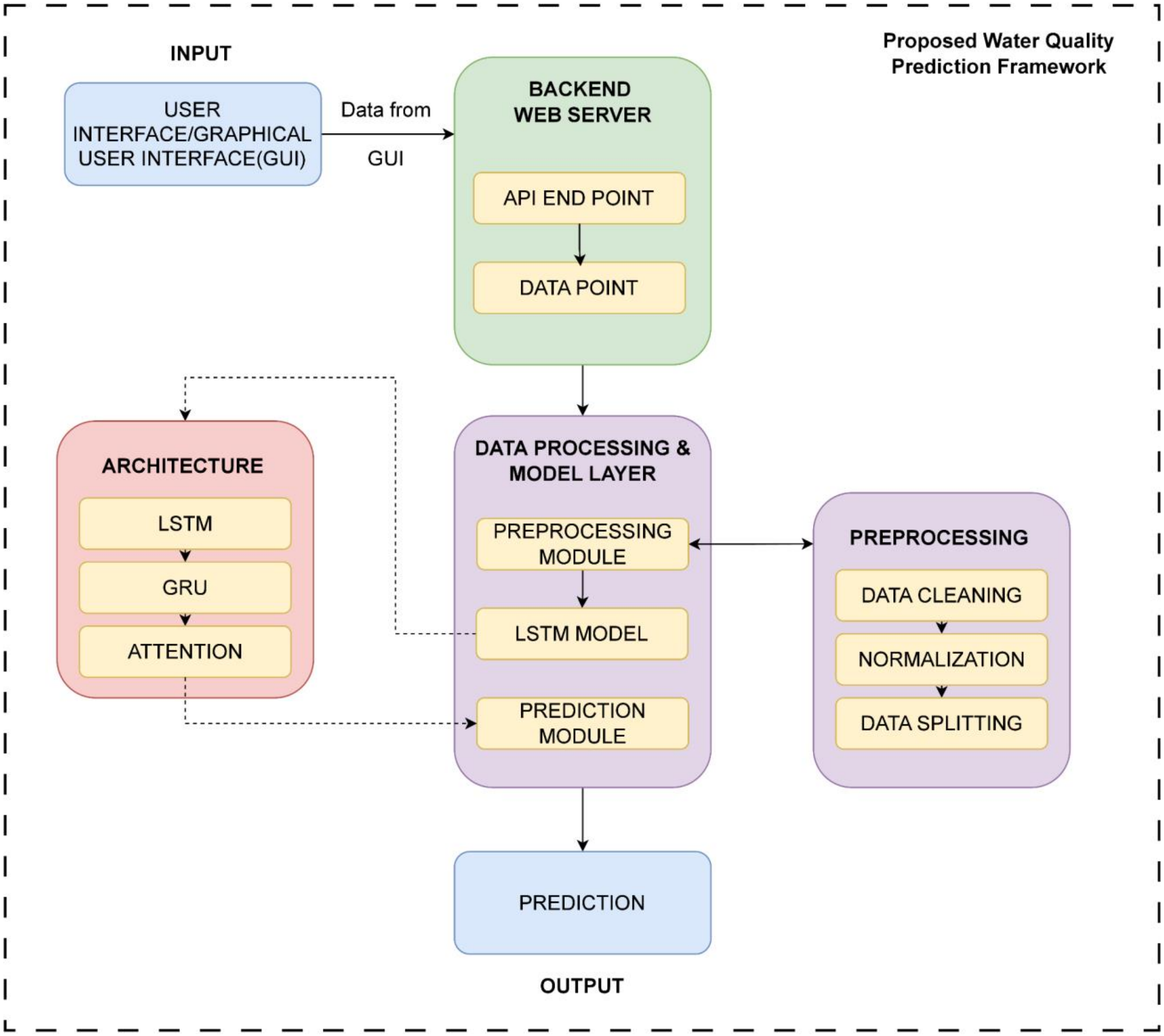

Fig. 1 Proposed LGA-Net framework for water quality analysis in Smart and Sustainable Aquaculture.

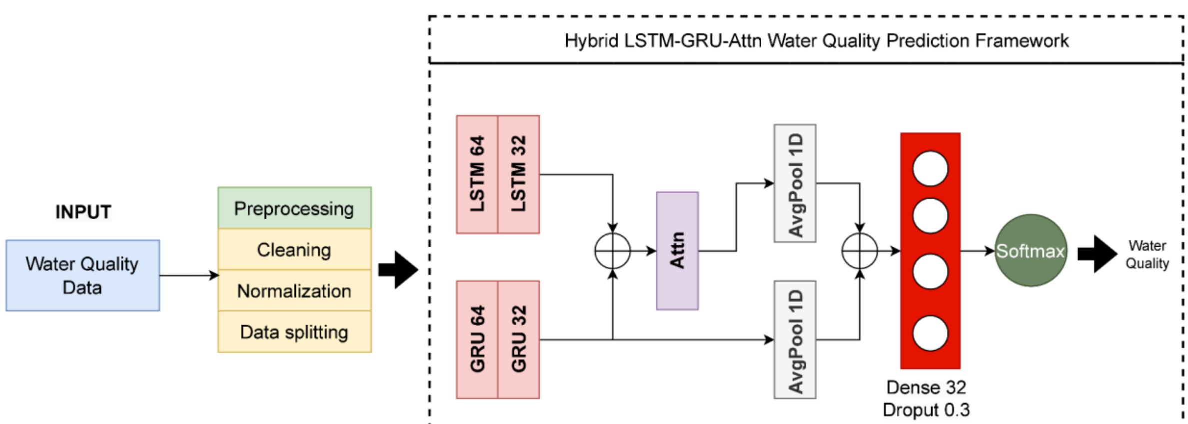

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Fig 2. The proposed LGA-Net Core Architecture

The core architecture of the proposed LGA-Net framework is given in Figure 2. The core predictive model consists of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, each with two layers (64 and 32 hidden units), designed to capture both short-term and long-term dependencies in sequential data. These outputs are then processed by an attention mechanism (Attn), which selectively emphasizes the most critical time steps, improving the model's interpretability and performance. Additionally, layers of 1D Average Pooling (AvgPool 1D) reduce dimensionality while preserving essential features. The extracted representations are then passed through a fully connected dense layer (32 units), followed by a Dropout layer (0.3) to prevent overfitting.

Finally, a softmax activation layer produces a probability distribution over different water quality categories, leading to a classification of the water quality status. The preprocessed data is passed to the Preprocessing Module, forwarded to the LSTM Model for learning the temporal patterns, and then to the Prediction Module, which creates the output. The output is then presented through the user interface (GUI), giving water quality status insights. The LGA-Net Framework efficiently processes time-series data with precise predictions using deep learning methods. Its well-defined pipeline, including a backend web server, preprocessing module, deep learning model, and user-friendly UI, makes it an extraordinarily scalable and effective solution for real-world water quality surveillance. This hybrid deep learning architecture enhances prediction accuracy and robustness, making it suitable for real-world water quality monitoring applications in innovative and sustainable aquaculture.

4. Experiment and Result Analysis

4.1 Dataset

The dataset has been specifically developed to train and evaluate deep learning models for assessing water quality in fish ponds based on key physicochemical parameters. A sample dataset is depicted in table 1. These parameters include Temperature, Turbidity, Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Carbon Dioxide (CO_2), pH, Alkalinity, Hardness, Calcium, Ammonia (NH_3-N), Nitrite (NO_2-N), Phosphorus, Hydrogen Sulfide (H_2S), and Plankton concentration. The dataset categorizes water quality into three distinct classes: Excellent, Good, and Poor. The classification is based on predefined threshold values that define acceptable, desirable, and stress ranges for optimal fish growth. Each sample is labeled accordingly, with Excellent quality assigned a value of 0, Good quality labeled as 1, and Poor quality designated as 2.

Temp	Turbidity (cm)	DO(mg/L)	BOD (mg/L)	CO2	pH`	Alkalinity (mg L-1)	Hardness (mg	Calcium (mg	Ammonia (mg L-1)	Nitrite (mg	Phosphorus (mg L-1)	H2S (m	Plankton (No. L-1)	Water Quality

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							L-1)	L-1)		L-1)		gL-1)		
67.45	**10.13**	**0.21**	**7.47**	**10.18**	**4.75**	**218.37**	**300.13**	**337.18**	**0.29**	**4.36**	**0.01**	**0.07**	**6070**	**2**
64.63	**94.02**	**11.43**	**10.86**	**14.86**	**3.09**	**273.94**	**8.43**	**363.66**	**0.10**	**2.18**	**0.01**	**0.02**	**251**	**2**
16.51	**25.57**	**7.66**	**5.80**	**3.54**	**6.30**	**47.54**	**30.05**	**102.44**	**0.05**	**0.03**	**0.02**	**0.01**	**2014**	**1**
19.88	**16.41**	**6.45**	**5.56**	**4.28**	**9.43**	**104.68**	**174.78**	**15.39**	**0.05**	**0.79**	**0.01**	**0.01**	**5395**	**1**
27.63	**60.00**	**5.00**	**1.56**	**6.72**	**8.45**	**59.65**	**89.79**	**85.70**	**0.01**	**0.01**	**0.10**	**0.01**	**4104**	**0**
27.64	**44.03**	**5.00**	**1.10**	**5.58**	**6.85**	**50.00**	**86.78**	**76.41**	**0.02**	**0.01**	**0.10**	**0.01**	**4344**	**0**

Table 1. The Water Quality Sample Dataset for Aquaculture

The dataset comprising 4,300 samples, which includes 1,500 poor-quality water samples, 1,400 excellent-quality samples, and 1,400 good-quality samples. Each record consists of 14 input features representing the water quality parameters and a single output label. This data, collected by Veeramsetty et al. (2024) and available at https://data.mendeley.com/datasets/y78ty2g293/1 , is a valuable resource for predictive model construction to observe and control aquaculture water quality. Researchers can enhance water quality assessment through deep learning techniques, creating a healthier and sustainable environment for fish culture. The desired parameter ranges for optimal aquaculture conditions are summarized in Table 2 below.

Parameter	**Desirable Range for Aquaculture**
Temperature	20–30°C (species-dependent)
Turbidity	30–60 cm (Secchi disk depth)

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Dissolved Oxygen (DO)	>5 mg/L (critical level: >3 mg/L)
Biochemical Oxygen Demand (BOD)	<5 mg/L
Carbon Dioxide (CO_2)	<10 mg/L
pH	6.5–8.5
Alkalinity	50–200 mg/L (as $CaCO_3$)
Hardness	50–150 mg/L (as $CaCO_3$)
Calcium	25–100 mg/L
Ammonia (NH_3-N)	<0.05 mg/L (toxic level: >0.1 mg/L)
Nitrite (NO_2-N)	<0.5 mg/L
Phosphorus	0.01–0.1 mg/L
Hydrogen Sulfide (H_2S)	<0.002 mg/L
Plankton (No. L^{-1})	20,000–100,000 cells/L (balanced for productivity)

Table 2. Desirable Ranges of Key Physicochemical Parameters for Aquaculture Water Quality

4.2 Performance of LGA-Net

The LGA-Net model effectively integrates LSTM, GRU, and attention mechanisms for time-series prediction in water quality monitoring. This section evaluates the performance of the proposed integrated model, LGA-Net, compared to individual models such as RNN, LSTM, and GRU.

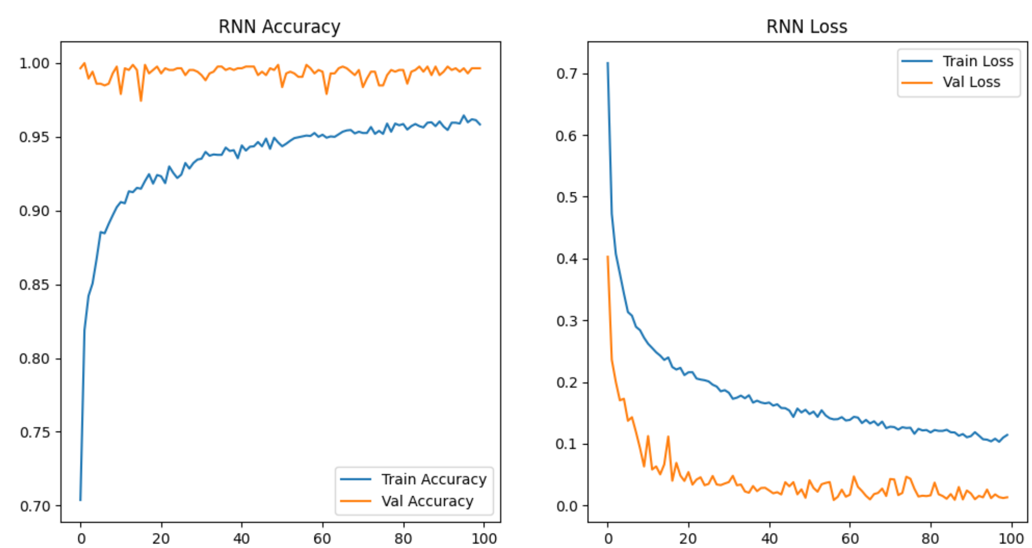

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Fig 4. Accuracy and Loss Characteristics for RNN

Figure 4 illustrates the accuracy and loss characteristics of the Recurrent Neural Network (RNN) model for innovative and sustainable water quality assessment. The left subplot depicts the accuracy trends over training epochs, where both training and validation accuracies show a steady improvement, with validation accuracy stabilizing at a higher value. The right plot shows the loss curves, which show a steady reduction in training and validation losses, demonstrating good learning and little overfitting. The results show the capability of the RNN model to predict water quality parameters accurately and thus be an appropriate method for sustainable aquaculture management.

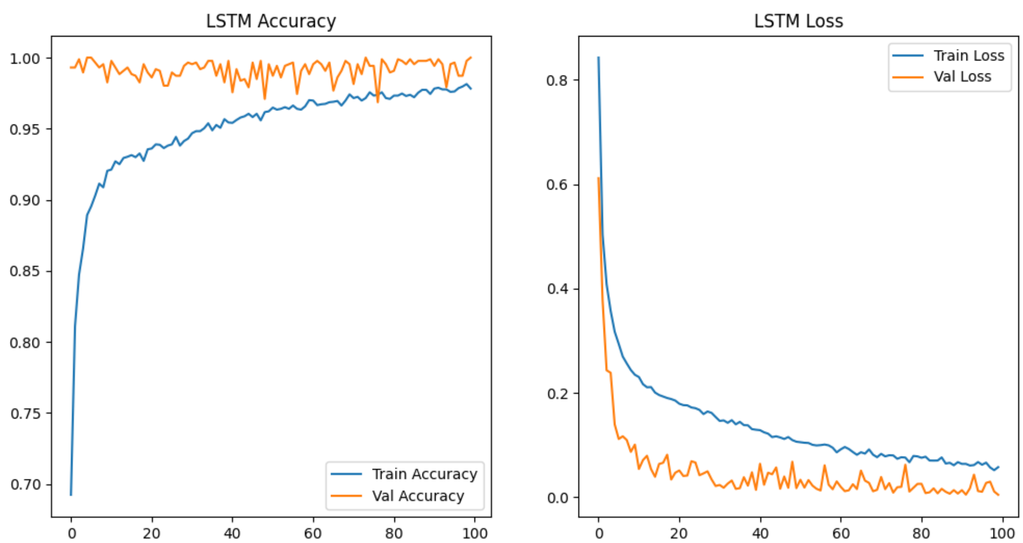

Fig 5:Accuracy and Loss Characteristics for LSTM

Figure 5 illustrates the accuracy and loss characteristics of the Long Short-Term Memory (LSTM) model for innovative and sustainable water quality assessment. The left subplot shows the training and validation accuracy trends over multiple epochs, with training accuracy steadily increasing and validation accuracy fluctuating but remaining consistently high. The right subplot illustrates the loss curves, presenting a steep decline in training and validation losses, reflecting successful learning and model convergence. The results highlight the capacity of LSTM to capture temporal relationships in water quality data, making it a potential tool for predictive analysis and sustainable water resource management.

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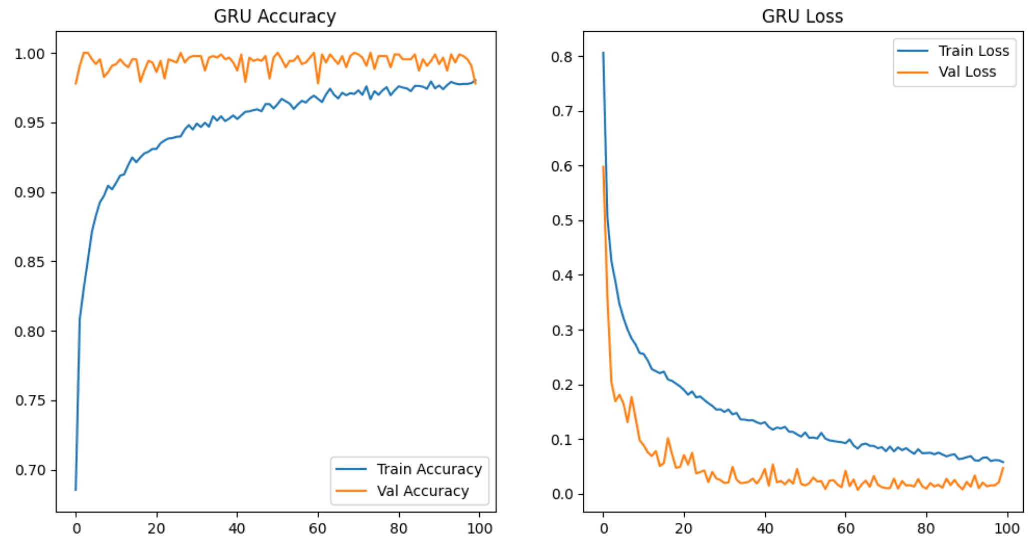

Fig 6:Accuracy and Loss Characteristics for GRU

Figure 6 presents the accuracy and loss characteristics of the Gated Recurrent Unit (GRU) model for water quality assessment. The left graph illustrates the training and validation accuracy trends, where training accuracy steadily increases and validation accuracy remains consistently high with minor fluctuations. The correct graph illustrates the loss curves, which indicate a steep drop in training and validation losses, illustrating successful learning and convergence. The GRU model demonstrates good performance, with rapid convergence and stable validation accuracy, and is thus an appropriate option for time-series prediction tasks in innovative and sustainable water quality monitoring.

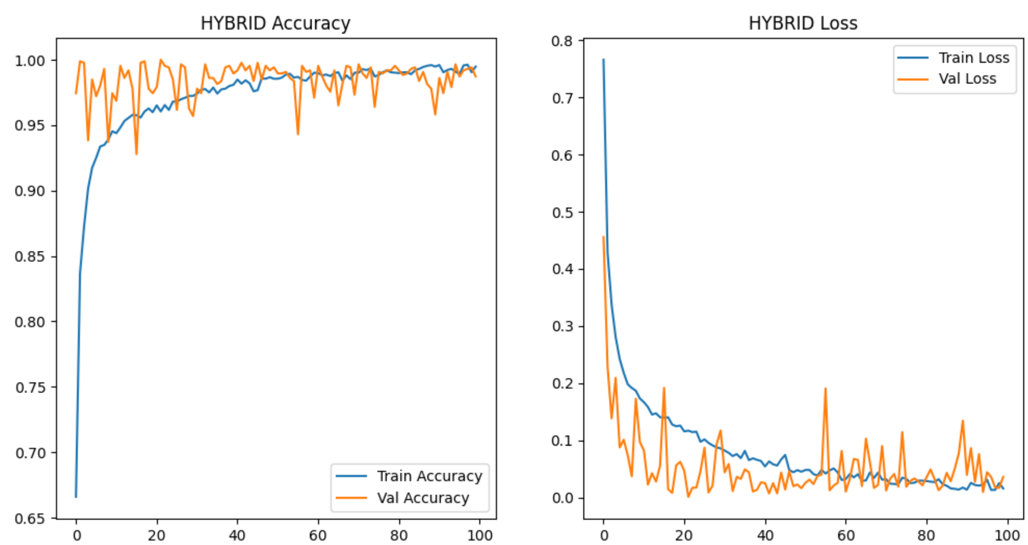

Fig 7:Accuracy and Loss Characteristics for LGA-Net: A LSTM-GRU-Attention Layer Hybrid Network for Water Quality Assessment in Smart and Sustainable Aquaculture.

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Figure 7 illustrates the accuracy and loss characteristics of the LGA-Net: A LSTM-GRU-Attention Layer Hybrid Network for Water Quality Assessment in Smart and Sustainable Aquaculture model. The left graph shows the training and validation accuracy trends, where both reach near-perfect accuracy, indicating strong model learning. The right graph presents the loss curves, demonstrating a sharp decline in both training and validation losses, with validation loss showing some fluctuations. The LGA-Net model effectively integrates LSTM, GRU, and attention mechanisms, leading to improved accuracy and stable convergence, making it a powerful approach for time-series prediction tasks in water quality monitoring.

Model	Accuracy	MSE	MAE	R2 Score
RNN	0.9784	0.0307	0.0247	0.9544
LSTM	0.9916	0.0147	0.0105	0.9783
GRU	0.9877	0.0270	0.0172	0.9600
LGA-Net	**0.9963**	**0.0114**	**0.0063**	**0.9831**

Table 3:Performance Evaluation of different models

The evaluation findings reveal the improved performance of the proposed LGA-Net model integrating LSTM, GRU, and an attention mechanism compared with individual LSTM, GRU, and RNN models. The LGA-Net model showed the best performance with the best accuracy (99.63%), lowest Mean Squared Error (MSE) of 0.0114, and lowest Mean Absolute Error (MAE) of 0.0063, demonstrating its highest prediction capability and least deviation from actual values. The R^2 score of 0.9831 indicates that the LGA-Net model effectively captures water quality parameters' variance. Among the individual models, LSTM performed better than GRU and RNN, with an accuracy of 99.16% and an R^2 score of 0.9783, followed by GRU, with an accuracy of 98.77% and an R^2 score of 0.9600. The RNN model, effective but the worst, reported an accuracy of 97.84% and an R^2 score of 0.9544, demonstrating slightly reduced predictive precision and generalization capacity. Overall, the findings verify that the LGA-Net model, synergistically integrating the strengths of LSTM and GRU and an attention mechanism, provides the most accurate and dependable predictions for water quality monitoring in aquaculture systems. Table 3 presents the performance results of different models.

Conclusion

The findings of the study point to the promise of intelligent and green deep learning models in revolutionizing aquaculture water quality monitoring. Traditional approaches are sporadic sampling-based and are likely to miss some of the most critical environmental changes in real-time, leading to unjustified losses. On the contrary, the proposed innovative deep learning model employs historical data to accurately forecast key water quality parameters. Of the models investigated, the LGA-Net deep learning model yielded the most accurate results, with the highest accuracy (99.63%) and lowest error margins (MSE: 0.0114, MAE: 0.0063, R^2: 0.9831), compared to single LSTM models, GRU models, and RNN models. The findings confirm the capability of artificial intelligence to enable proactive decision-making, reduce intervention efforts, and ensure smart and sustainable aquaculture management. Aquaculture practitioners can leverage real-time predictive intelligence to optimize water conditions, improve productivity, and contribute to global food security through smart, sustainable, and resilient fisheries management.

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