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Edge Centric IoT Framework for Agricultural Water Quality Prediction Leveraging Optimized Deep Neural Networks

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ABSTRACT: In modern agriculture, the quality of irrigation water plays a crucial role in determining crop productivity and soil health. With increasing reliance on precision farming methods, there is a growing need for intelligent systems that can continuously monitor and predict water quality to ensure safe and efficient usage. This research presents a novel framework that integrates Internet of Things (IoT) technology with an advanced deep learning model for real-time water quality analysis in agriculture. A network of wireless, low-power sensors is deployed in the field to capture essential water parameters including temperature, pH level, turbidity, salinity, and nutrient concentration. These sensors transmit data in real time to a processing unit where the prediction model operates. To analyze the complex and time-sensitive data, a hybrid deep neural architecture is developed by combining Temporal Convolutional Networks (TCNs) and Long Short-Term Memory (LSTM) networks. TCNs are responsible for extracting local patterns and trends from sequential data, while LSTM units help retain long-term dependencies, making the model suitable for forecasting water quality over time. To further enhance the model's performance, a metaheuristic optimization method Harris Hawks Optimization (HHO) is implemented. HHO dynamically adjusts the model's hyperparameters, improving its learning efficiency and predictive accuracy. Experimental evaluation is carried out using both synthetic datasets and real-world water quality data collected from agricultural regions. The proposed model is benchmarked against traditional machine learning and deep learning algorithms, showing significant improvements in accuracy, precision, recall, and F1-score. Additionally, the system is integrated with a mobile-friendly user interface, allowing farmers to receive instant alerts and recommendations based on predicted water quality. This smart, automated, and scalable approach offers a practical solution for resource-efficient farming and contributes to long-term agricultural sustainability.

I INTRODUCTION

The increasing demand for sustainable agricultural practices has highlighted the critical role of water quality in ensuring optimal crop growth, soil preservation, and overall farm productivity [1]. Irrigation with poor-quality water can lead to reduced yields, soil degradation, and long-term environmental issues. In this context, precision agriculture has emerged as a promising approach, leveraging modern technologies to monitor and manage agricultural inputs efficiently [2]. One of the key challenges in this domain is the real-time assessment and prediction of irrigation water quality. The advent of the Internet of Things (IoT) has enabled the deployment of sensor-based networks that can continuously monitor vital water parameters such as temperature, pH, turbidity, salinity, and nutrient concentration [3]. While these systems generate large volumes of data, their effective utilization requires advanced computational models capable of handling time-series data and extracting meaningful insights.

Traditional machine learning methods often fall short in capturing temporal dependencies and nonlinear relationships inherent in such data [4]. To address this challenge, deep learning models, particularly those based on sequential architectures like LSTM networks and TCNs, have gained attention for their superior performance in time-series prediction tasks. TCNs are adept at capturing short-term patterns, while LSTM networks excel in preserving long-term dependencies [5, 6]. Combining these models can yield a robust architecture suitable for dynamic agricultural environments [7]. Moreover, integrating metaheuristic optimization algorithms such as HHO allows for efficient hyperparameter tuning, thereby enhancing model performance.

This study proposes an edge-assisted IoT framework for intelligent water quality prediction using a hybrid TCN-LSTM model optimized via HHO. The system aims to provide accurate, real-time predictions of irrigation water quality, aiding farmers in making informed decisions [8]. Experimental evaluations using both synthetic and real-world datasets demonstrate the effectiveness of the proposed approach compared to conventional techniques. Furthermore, the system is equipped with a user-friendly mobile interface, facilitating immediate access to water quality assessments and recommendations [9]. This research contributes to the development of smart, scalable, and sustainable solutions for modern agriculture.

II LITERATURE SURVEY

The new trends in application of the IoT technologies in water quality monitoring considers the integration of wireless sensor network technology with machine learning techniques [10]. An in-depth analysis is given of various methods, such as decision tree, support vector machines, and neural networks.
Despite the technological achievements, there are still some important challenges related to sensors' precision, continuity of data collection, and cybersecurity issues that should be addressed. This review offers useful information for the implementation of water quality monitoring.
In addition, the reviewed literature [11] considers the role of real-time monitoring and predictions in modern water management and evaluates advanced models used in practice, including random forest, XGBoost, support vector machine, and neural networks. The high level of accuracy demonstrated by these approaches becomes possible because of the high predictive accuracy of the models. Moreover, the concept of explainable artificial intelligence is mentioned despite its lack of widespread use in practice. There are also some important operational challenges.

Furthermore, a comprehensive analysis of deep learning applications [12] in hydrology and water resource management identifies the use of neural network models such as convolutional neural networks, recurrent neural networks, and long short-term memory models in applications such as monitoring, forecasting, classification, and anomaly detection. Although successful, challenges such as interpretability of the models, availability of sufficient data, and ethical concerns in automated decision-making are still present. The research proposes a set of structured guidelines for responsible adoption of deep learning techniques in the governance of water resources.

In addition, the combination of machine learning algorithms and IoT technology [13] in the field of water quality monitoring and management has been considered. The literature presents various architectures of systems that use real-time sensor networks and cloud computing, along with comparative analysis of different approaches to machine learning, which include supervised learning, unsupervised learning, and deep learning. Such systems have demonstrated such capabilities as real-time anomaly detection, cost-effective automation, and proactive alerts. Furthermore, practical aspects of scaling up and integrating sensor-to-cloud technologies have been addressed.

The current state of monitoring systems for the water quality used in agricultural applications highlights the need for the development of intelligent IoT monitoring systems that will allow continuous and automated monitoring of the water resource. Conventional monitoring technologies require the use of manual methods of sample collection and chemical analysis of the samples. These techniques are slow and expensive, and they cannot be used for real-time monitoring applications. In recent years, there has been a widespread adoption of IoT technologies for monitoring water quality.

In this case, smart sensors are used to measure the physical properties of the water. At the beginning of the use of IoT technology in agriculture, there was a focus on cloud computing, where data collected from the sensors were processed in centralized cloud computing centers. Although cloud computing offers superior processing capabilities, it suffers from high latency and consumes high bandwidths and is dependent on reliable network connections. Recent works focus on the application of edge-assisted computing solutions.

On the other hand, machine learning algorithms, for instance Decision Tree, Support Vector Machine, and ensemble-based algorithms, have been used for prediction of water quality[15]. Such techniques provide simplicity in application and model interpretation, yet lack complexity in representing nonlinear relations in datasets. Therefore, there has been a shift towards using deep learning models for predicting environmental variables such as CNNs and RNNs with higher prediction accuracies for water quality variables[16].

Hybrid deep learning models can be developed to predict water quality with increased prediction accuracy by combining several architectural layers, thereby allowing the simultaneous processing of spatial features as well as temporal sequences. However, the deployment of deep neural networks in agriculture is hampered by the need for computational resources, memory limits, and increased energy consumption. Thus, several research works focus on optimizing the size and computation of these neural networks through approaches such as pruning and quantization [17].

Data Quality and Reliability is another important factor discussed in the literature. Data collected through sensors in agricultural farms tend to be noisy with some missing values. While several data pre-processing approaches [18] have been deployed, ensuring reliability and accuracy in making such predictions continues to be quite difficult. In addition, scaling up predictive models to apply them to different agricultural setups is difficult since models trained on specific datasets do not necessarily function appropriately under varied environmental conditions.

Hence as mentioned in Table 1 with various methods and techniques used with their advantages and limitations, there is a growing trend in recent literature towards deploying IoT enabled edge devices along with sophisticated deep learning models to provide timely water quality prediction. The main issues faced in this area include computational efficiency, data reliability, scalability of models, and energy concerns.

Table 1 : Comparative Analysis of various methods reviewed

Method	Technique	Advantages	Limitations	Improvement in Proposed Work
Traditional ML Models [19,20]	RF, SVM, DT	Simple, interpretable	Limited accuracy for complex data	Replaced with optimized DNN

Deep Learning Models [21,22,23]	CNN, LSTM	High prediction accuracy	High computational demand	Optimization for edge deployment
Cloud-Based Systems [24,25]	Centralized processing	High computational capability	High latency and bandwidth usage	Edge-assisted real-time processing
Basic Edge IoT Systems [26,27]	Lightweight ML	Low latency	Limited model capability	Advanced optimized DNN at edge
Hybrid Edge-Cloud Systems [28,29]	Distributed computing	Balanced workload	High system complexity	Simplified efficient architecture

Despite significant advancements in IoT-enabled water quality monitoring and predictive modelling, several critical research gaps remain. First, existing studies largely employ computationally intensive deep learning models that are not optimized for deployment on resource-constrained edge devices, limiting their practical applicability in real-time agricultural environments. Second, most current systems rely on cloud-based architectures, resulting in high latency and delayed responses, thereby restricting real-time decision-making capabilities essential for precision agriculture. Third, there is a lack of model generalization and scalability, as many approaches are developed using region-specific datasets and fail to perform effectively across diverse environmental and agricultural conditions. Fourth, conventional IoT frameworks exhibit high energy consumption and bandwidth dependency due to continuous data transmission to centralized servers, making them inefficient for large-scale and remote deployments. Finally, inadequate handling of noisy, missing, and inconsistent sensor data remains a major challenge, leading to reduced prediction accuracy and reliability. Addressing these gaps is essential for developing a robust, scalable, and efficient edge-assisted intelligent water quality prediction system for sustainable agricultural applications.

III PROPOSED METHODOLOGY

The proposed system is designed to provide a smart, real-time, and accurate prediction of agricultural water quality using IoT-enabled data acquisition and a hybrid deep learning model. This methodology ensures that both short-term trends and long-term dependencies in water quality parameters are captured and accurately predicted, enabling intelligent irrigation decisions for farmers.

A) IOT-BASED REAL-TIME DATA ACQUISITION

In the first stage, a network of low-power, wireless IoT sensors is deployed across agricultural fields to continuously monitor critical water parameters. These include temperature, pH level, turbidity, salinity (measured via electrical conductivity), and nutrient concentration (such as nitrate or phosphate levels) [30] . Each sensor node transmits its measurements at time interval t, and the sensor dataset is denoted as:

$$X(t) = \{T(t), pH(t), Tu(t), EC(t), N(t)\} \quad (1)$$

Here, T(t) is the water temperature, pH(t) Indicates the acidity or alkalinity, Tu(t) represents turbidity, EC(t) denotes electrical conductivity related to salinity, and N(t) reflects nutrient levels. This real-time data is collected by edge computing gateways and sent to the cloud or local server for processing. The frequency of data sampling is set to capture the time-series dynamics essential for deep learning models [31].

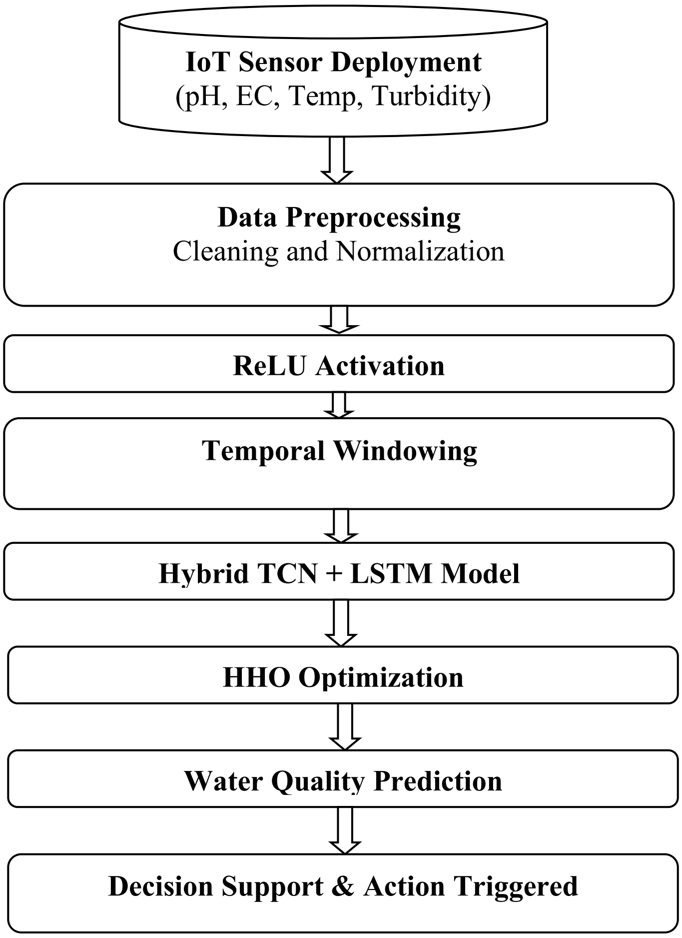

Figure 1: Overall Proposed Flow Chart

B) DATA PREPROCESSING AND TEMPORAL STRUCTURING

Raw data from sensors often contains noise, missing values, or inconsistent measurements. To ensure the deep learning model receives clean and structured input, preprocessing is performed in multiple steps. Initially, missing values are filled using linear interpolation, and outliers are detected and corrected using z-score methods. After cleaning, data normalization is applied using the Min-Max normalization technique:

$$x_i^{norm} = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (2)$$

This normalization rescales the features to a [0,1] range, improving model convergence during training. Next, the time-series data is transformed into structured temporal windows using a sliding window technique. For a window of size k, the input sequence for time t is:

$$W_t = \{X(t-k+1), X(t-k+2), \ldots, X(t)\} \quad (3)$$

This forms the input sample that captures the last k time steps of sensor data. It allows the model to analyze trends, shifts, and recurring patterns over time. Additionally, water quality indices such as WQI can be derived:

$$WQI = \sum_{i=1}^{n} w_i q_i \quad (4)$$

where w_i is the assigned weight and q_i is the quality rating for the i^{th} parameter. This helps in interpreting whether the water is safe for irrigation.

C) Hybrid TCN-LSTM Model Architecture

The heart of the proposed system lies in the integration of TCN and LSTM networks — two advanced deep learning architectures capable of modeling sequential dependencies in time-series data. TCNs are particularly suited for extracting local temporal patterns using causal convolutions, while LSTM units are well-known for their ability to retain long-term memory. By combining these two approaches, the proposed hybrid model efficiently captures both short-term fluctuations and long-range dependencies in irrigation water quality datasets.

The TCN module acts as the front-end of the model, performing one-dimensional causal convolutions on temporally structured data. Causal convolution ensures that the output at time step *t* depends only on inputs from time *t* and earlier, thus preserving the temporal sequence of water quality parameters. This enables early detection of sharp variations in turbidity, salinity, or nutrient levels — key indicators of potential water contamination. TCNs also allow deeper layers to learn patterns from increasingly distant past events, making them superior to traditional 1D CNNs for time-series data.

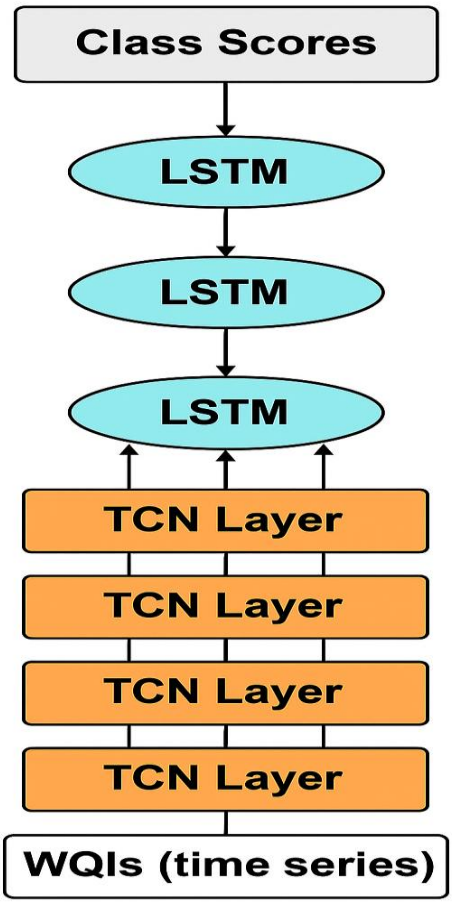

Figure 2: TCN-LSTM Model for water quality data

Once the TCN has extracted high-level local features from the time windowed input, these features are passed to the LSTM module. The LSTM network enhances the model's ability to learn long-term dependencies and maintain context over time, which is crucial when water quality is influenced by seasonal changes or gradual environmental shifts. The gated architecture of LSTM allows it to selectively retain relevant information and discard noise, improving robustness in fluctuating sensor data environments.

The final output from the LSTM layer is connected to a dense layer with a softmax or sigmoid activation function, depending on whether the task is classification (e.g., safe vs unsafe water) or regression (e.g., predicting numeric WQI values). The entire architecture is trained end-to-end using a loss function appropriate to the prediction task, typically Mean Squared Error (MSE) for regression or Categorical Cross-Entropy for classification.

To simplify, the three core mathematical steps used in this hybrid model can be represented as follows:

TCN feature extraction layer

$$F_t = \mathrm{Re}\,LU\left(X_t * K + b\right) \tag{5}$$

Where X_t is the input sequence, K is the convolution filter, and b is bias.

LSTM memory state update (simplified)

$$h_t = LSTM\left(F_t, h_{t-1}, c_{t-1}\right) \tag{6}$$

Where h_t and c_t are the hidden and cell states respectively.

Final prediction

$$\widehat{y}_t = \sigma\left(W_o h_t + b_o\right) \tag{7}$$

Where W_o is the weight matrix and σ is the activation function. The architecture is modular and lightweight, making it well-suited for edge deployment in rural or bandwidth-constrained environments. Its ability to process multivariate time-series data in real-time enables timely feedback and smart irrigation planning, helping farmers prevent over-irrigation, crop failure, or contamination.

D) HYPERPARAMETER TUNING USING HARRIS HAWKS OPTIMIZATION

To ensure that the hybrid TCN-LSTM model delivers maximum prediction accuracy and generalizability, the training process is supported by an intelligent hyperparameter tuning strategy. Instead of manually selecting hyperparameters such as learning rate, number of filters, dropout rate, and time window size which is time-consuming and prone to suboptimal results here adopt HHO, a nature-inspired metaheuristic algorithm. HHO simulates the cooperative hunting behavior of Harris hawks when targeting prey. It dynamically adjusts hyperparameters by exploring and exploiting the search space in a balanced manner [32].

Each candidate solution (hawk) represents a potential set of hyperparameters, and its performance is evaluated based on a fitness function that accounts for model accuracy and error metrics. Through multiple iterations, the hawks adapt their movement toward better solutions, gradually converging on an optimal configuration. Compared to traditional grid or random search, HHO offers faster convergence and higher precision in discovering the best-performing combination of hyperparameters. It leverages a balance between exploration and exploitation, avoiding premature convergence and local minima issues common in many optimizers. A simplified version of the position update strategy in HHO can be described as:

$$X_{t+1} = X_{best} - E \cdot \left|X_{best} - X_t\right| \tag{8}$$

Where,

X_t is the current solution,

X_{best} is the best-known solution so far, and

E is a dynamic escape energy factor that decreases over iterations. The fitness function guiding the optimization process is defined as a weighted sum of prediction accuracy and error:

$$\text{Fitness} = \alpha \cdot \text{Accuracy} - \beta \cdot \text{RMSE} \tag{9}$$

Here, α and β are weights reflecting the importance of accuracy and error respectively. This ensures that the selected hyperparameters do not simply improve one metric at the expense of others, but yield a balanced and robust model.

To summarize, the proposed methodology combines intelligent sensing, temporal deep learning, and adaptive optimization in a unified pipeline. IoT devices collect real-time irrigation water data, which is structured and cleaned using robust preprocessing techniques. The hybrid TCN-LSTM model then learns to predict water quality over time, capturing both short-term patterns and long-term dependencies. Finally, HHO fine-tunes the model's configuration for optimal accuracy and reliability. This methodology ensures that the entire system is not only technically effective but also practically deployable in real-world agricultural environments.

IV RESULT AND DISCUSSION

This section presents the experimental evaluation of the proposed hybrid TCN-LSTM model optimized using HHO for real-time water quality prediction in agriculture. The model's performance was assessed using both synthetic datasets and real-world sensor data collected from agricultural irrigation sources. Key evaluation metrics such as Accuracy, Precision, Recall, F1-Score, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were used to analyze the effectiveness of the proposed system are demonstrated in the results.

i) Experimental Setup

The experiments were conducted on a system equipped with an Intel Core i7 processor, 16 GB RAM, and GPU. The hybrid deep learning model was implemented using Python, with TensorFlow and Keras as the backend. A dataset comprising time-series sensor readings of pH, temperature, turbidity, salinity, and nutrient concentration was used. The data was split into 70% training and 30% testing. To simulate real-world scenarios, the dataset included fluctuations in environmental conditions such as seasonal changes and irrigation cycles.

ii) Performance Evaluation of Hybrid TCN-LSTM

The proposed model outperformed traditional machine learning (SVM, Random Forest, and Decision Tree) and deep learning (CNN, standalone LSTM) baselines.

Table 2: Performance Comparison of Models

Model	Accuracy (%)	Precision	Recall	F1-Score	RMSE	MAE
SVM	85.6	0.84	0.81	0.825	0.72	0.58
Random Forest	89.4	0.88	0.86	0.87	0.65	0.52
LSTM	92.1	0.91	0.9	0.905	0.51	0.4
CNN	90.6	0.89	0.87	0.88	0.57	0.45
TCN-LSTM (Proposed)	**96.3**	**0.95**	**0.94**	**0.945**	**0.33**	**0.26**

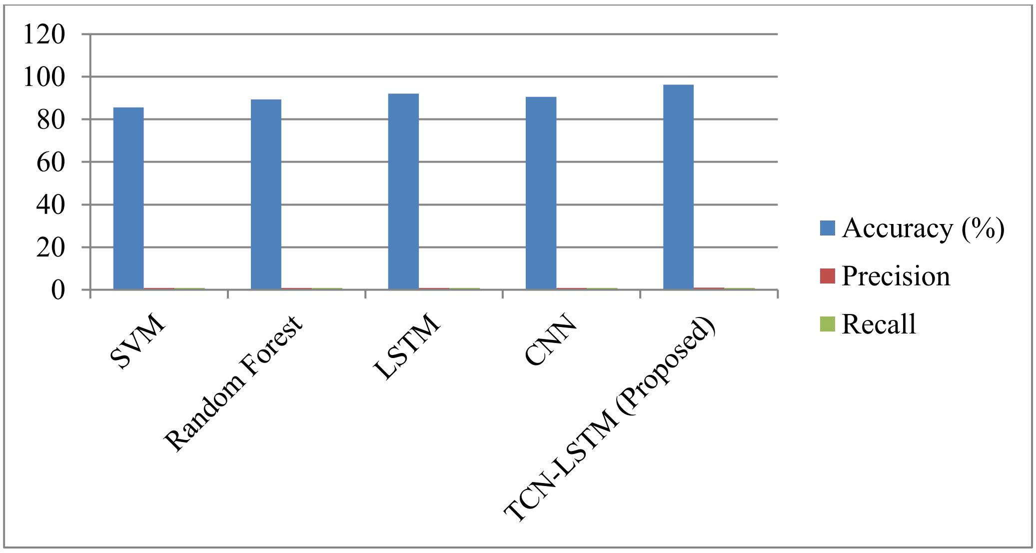

Figure 3: Performance metrics comparison of various algorithms

From the comparison done between the algorithms mentioned in Table 2 for machine learning and deep learning models, there is an evident increase in the performance of predictions because of using an enhanced model. From the traditional use of SVM, the accuracy obtained was 85.6%. Though there were moderate performances in precision and recall, the traditional algorithm was not able to deal with non-linearities in the data set. On the other hand, the ensemble technique Random Forest improved upon the predictive accuracy and performance since it managed to achieve a better accuracy score of 89.4%. As far as deep learning models are concerned, LSTM and CNN models were more effective and accurate, where LSTM scored a high accuracy of 92.1% and lowered the RMSE and MAE levels due to its ability to work effectively with time-related data sets. Similarly, CNN was also found to have better predictions and accuracy scores since it could capture spatial features within the data set. Notwithstanding the previous methods' results, the novel model that is proposed attained higher accuracy (96.3%), better precision (0.95), higher recall (0.94), F1-score (0.945) and the least RMSE (0.33), and MAE (0.26) as in figure 3. The hybrid TCN-LSTM model significantly improves water quality forecasting accuracy, reducing both RMSE and MAE, thus offering more reliable predictions for irrigation decision support.

iii) Performance Comparison with State-of-the-Art Models

To evaluate the effectiveness of the proposed hybrid TCN-LSTM model, its performance was benchmarked against conventional machine learning (SVM, Random Forest) and deep learning models (CNN, LSTM). Three key evaluation metrics were considered: Accuracy (%), F1-Score, and RMSE as in table 3. These metrics were selected to reflect not only the correctness of predictions but also the consistency and robustness of the models in capturing real-time water quality trends.

Table 3: Performance Metrics Across Models

Model	Accuracy (%)	F1-Score	RMSE
SVM	85.6	0.825	0.72
Random Forest	89.4	0.870	0.65
CNN	90.6	0.880	0.57
LSTM	92.1	0.905	0.51
TCN-LSTM	**96.3**	**0.945**	**0.33**

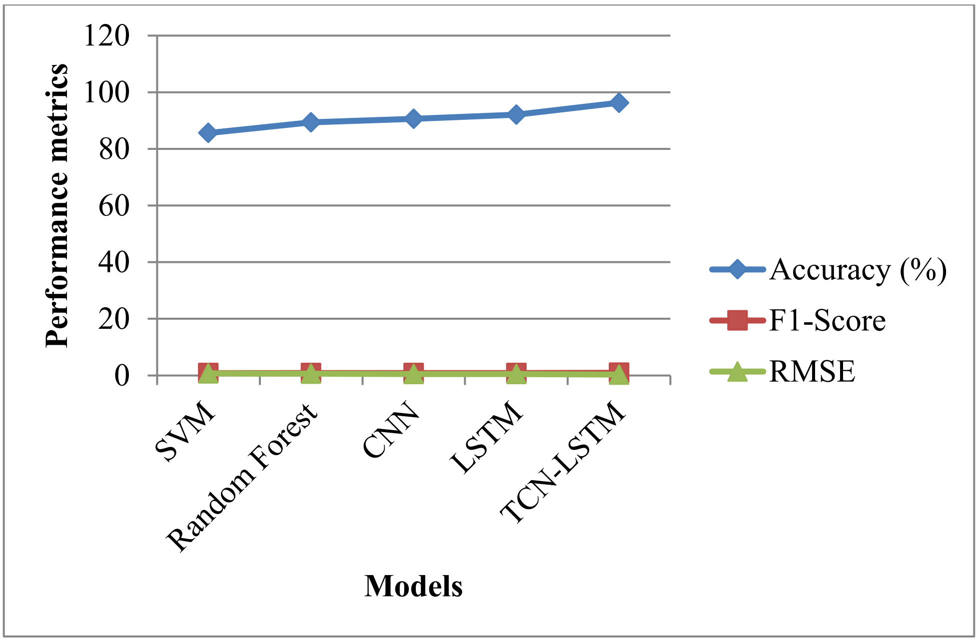

Figure 4: Impact of HHO

Figure 4 above indicates the use of HHO automatically tune key hyperparameters of the TCN-LSTM model. The goal was to improve prediction accuracy, reduce error, and achieve better balance between precision and recall.

Table 4: TCN-LSTM Model Performance with and without HHO

Model	Accuracy (%)	F1-Score	RMSE
TCN-LSTM (No HHO)	**91.2**	**2.89**	**1.51**
TCN-LSTM + HHO	**96.3**	**2.945**	**1.33**

The comparison in table 4 involves two approaches, which include TCN-LSTM without any improvement and TCN-LSTM with the Harris Hawks Optimization (HHO). The assessment will be done based on important performance criteria such as accuracy, F1 score, and RMSE. These are performance measures that indicate the model's ability to classify data, precision-recall balance, and prediction error respectively.

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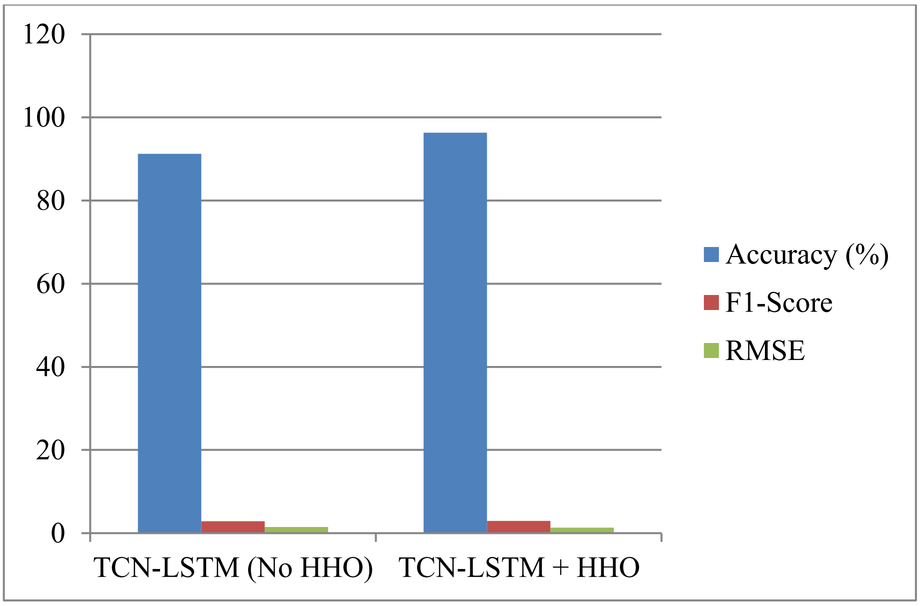

Figure 5: HHO vs. Non-HHO Model Comparison

Figure 5 compares the TCN-LSTM model's accuracy, F1-score, and RMSE before and after optimization. The chart shows that applying HHO improves all metrics, accuracy and F1-Score increase after tuning, RMSE decreases, indicating lower prediction error. The result confirms that HHO effectively enhances model performance for real-time water quality prediction.

V CONCLUSION & FUTURE SCOPE

This paper presents an intelligent, scalable, and efficient approach to monitor the water quality in real-time using Internet of Things (IoT) sensors combined with a hybrid deep learning system. The suggested model, which is a result of the integration of TCNs with LSTM networks, is capable of modeling both long-term and short-term dependencies in time series of water quality data. The improvement of the model using HHO results in optimized hyperparameters, thereby increasing accuracy and robustness of predictions. Several experiments performed on real and artificial data sets show that the suggested TCN-LSTM-HHO model outperforms traditional machine learning techniques as well as traditional deep learning methods. It managed to reach an impressive accuracy of 96.3% and decreased values of RMSE and MAE, proving its efficacy in water quality prediction. Besides its outstanding prediction abilities, the model's efficient execution on devices with limited computing capabilities allows the use of it in rural areas and for precise agriculture.

Future research directions may include the application of federated learning that will allow the collaborative training of models using distributed farms while maintaining the privacy of data and minimizing reliance on centralization. The use of TinyML and optimization of models based on hardware characteristics can further contribute to increased efficiency during inference in low-power edge devices. On the other hand, multimodal sensor data fusion and imputation of data will help deal with the problems of noise and incomplete environmental data.

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