Design and Development of An Automated IoT-Aided Smart Agriculture Management System for Efficient Crop Yield Prediction

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Abstract. Crop yield forecasting is a fundamental part of current precision agriculture which enables sustainable farming practice and optimal resources scheduling. Combining IoT with deep learning can improve predictive performance by benefiting from the real-time data gathering and the power of computational models. In this study, an IoT-based crop production forecasting framework is introduced which uses the LEO, during the progress of the system to effectively route the data, so that the energy consumption will be minimum and the data transmitted is precise. The collected data is pre-processed and features are extracted by a Temporal Convolutional Network (TCN) to capture long-range dependencies of agricultural-related data. These representations are passed to a hybrid BiLSTM-WANN network which integrates a BiLSTM to capture the time dependency followed by a WANN network that optimizes the model structure without weight updates. What is more, we also propose to LEO to update weight parameters in order to reduce prediction error and increase accuracy. This implication results in an efficient, scalable, and high-performance architecture for crop yield prediction. The performance of the proposed method is MSE=0.0082 and MAE=0.003 less than that of the existing methods. Through the combination of optimized routing, deep learning, and metaheuristic optimization, the system improves the agricultural decision-making process, resource use optimization, and environmentally friendly farming, positioning itself as an asset in precision agriculture.

Keywords: Crop Yield Prediction, Deep Neural Network, Internet of Things, Lotus Effect Optimization Algorithm, Smart Agriculture Management System.

1 Introduction

Crop manufacturing is the spine of global food safety, presenting sustenance and economic balance for tens of millions [1]. It encompasses the cultivation of plants for food, fiber, and other sources essential to human lifestyles [2]. However, agricultural productiveness is especially dependent on different factors consisting of weather, soil conditions, water availability, and farming strategies [3]. One important indicator of agricultural productivity is crop yield, which is the quantity of agricultural products harvested per unit of land [4]. Predicting crop yield appropriately is important for ensuring meal safety, efficient and useful resource control, and financial planning [5]. However, conventional strategies of crop yield

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prediction, which rely upon statistical fashions and ancient records, are often time-consuming and much less powerful in addressing the complexities of current agriculture [6]. The creation of big records and synthetic intelligence has led to the improvement of advanced system studying fashions that decorate the accuracy of crop yield forecasts by means of reading massive datasets [7]. One of the most promising improvements in this domain is the mixing of the Internet of Things (IoT) into agriculture, leading to the idea of clever agriculture management systems [8]. IoT-primarily based agriculture control structures make use of a network of smart sensors, cloud computing, and real-time data analytics to reveal various environmental parameters, consisting of soil moisture, temperature, humidity, and climate conditions [9]. These structures assist farmers in making informed choices by supplying timely insights into crop fitness, irrigation needs, and pest control techniques [10]. In the context of crop yield prediction, IoT plays an important function through constantly amassing and transmitting real-time agricultural information, which can be processed with the use of device mastering algorithms [11].

Several challenges remain for IoT smart agriculture systems. Keeping up IoT apparatus, especially for smallholders' farmers might also be difficult. The continuous data exchange through networks lead to privacy and security concerns. Also, how to fuse heterogeneous sensor data, translate the information to feedback commands, and translate between different platforms is yet an open problem in the technical field.

The rapid advance of deep learning and the Internet of Things offers a revolutionary opportunity to advance agricultural sustainability and increase yields. Real-time data enables farmers to make informed decisions about how to optimize resource efficiencies and improve crop output estimates. Robot-controlled smart greenhouses can also help in automating tasks and can also lead to labour saving and reduced wastage for sustainable farming. Global food demand is rising, so effective means of agriculture are required to sustain food security. Adoption of IoT-based smart agriculture can convert standard agri-cultivation into 'smartified' and monitor crops conditions while responding to the environmental changes specifically. The main contributions are summarized as:

- The objective is to develop an efficient and accurate IoT-driven crop yield prediction system by integrating optimized data routing, advanced feature extraction, and hybrid deep learning models.
- The proposed system leverages IoT sensors to collect real-time agricultural data and employs the LEO algorithm for efficient routing, ensuring reliable data transmission with minimal energy consumption.
- The TCN efficiently extracts long-range dependencies in time-series agricultural data, preserving sequence integrity while reducing computational complexity.
- A hybrid BiLSTM and WANN model enhances crop yield prediction by capturing sequential dependencies and optimizing network architecture without traditional weight training.
- The LEO algorithm further refines model weights, reducing prediction errors and enhancing accuracy, making the system more efficient for large-scale agricultural applications.

The structure of the remaining sections is as follows: Literature survey for crop yield prediction is defined in Section 2. A proposed prediction model is presented in Section 3. Outcome and Analysis is covered in Section 4, and a conclusion is provided in Section 5.

2 Literature Survey

In 2023, F.M. Talaat [12] has an approach of Crop Yield Prediction Algorithm (CYPA). Understanding the cumulative effects of field elements like as pests, illnesses, and water and nutrient deficits during the growing season is made easier by simulating crop yields.

In 2023, A.H. Eneh et al. [13] have focused on enhancing a mobile aquaponics system that integrates aquaculture and crop production by reusing wastewater efficiently. It addresses the lack of datasets on growth monitoring in Sub-Saharan Africa, which affects yield management and prediction.

In 2023, S. Kiruthika and D. Kiruthika [14] have suggested an IoT-based system using hybrid optimization for feature selection and Weighted LSTM for crop prediction. It processes climate and crop yield data, enhances input quality through pre-processing, and selects the most relevant features for accurate predictions.

In 2024, L.K. Subramaniam and R. Marimuthu [15] focused on improving prediction in the region of Indian crops using deep learning and dimensionality reduction techniques.

In 2023, A.B. Sarr and B. Sultan [16] have suggested a machine learning-based crop output prediction for Senegal to improve early warning systems in the face of climate change.

2.1 Problem Statement

Accurate data collection, sensor dependability, and the smooth integration of real-time environmental elements are some of the issues facing the IoT-assisted smart agriculture management system for crop yield prediction. Traditional methods fail to incorporate dynamic soil and climate conditions, leading to inaccurate yield forecasts. Smart IoT-based systems, combined with advanced machine learning models, enhance predictive accuracy but are hindered by data quality, network failures, and computational efficiency. Variability in weather patterns, pest infestations, and limited internet connectivity in remote areas further complicate precision forecasting. Ensuring the security, interoperability, and power efficiency of IoT devices is critical for system reliability. To address these challenges, this proposes a BiLSTM with a WANN-based IoT framework for efficient and adaptive crop yield prediction. The goal is to develop a scalable and accurate system that enhances agricultural productivity and sustainability.

3 Proposed Methodology

For crop yield prediction starts with IoT simulation that has input of LEO routing. This routing system takes network efficiency as its fitness function, and the data is forwarded to a Base Station (BS), at the same time the input is received from dataset and preprocessed. The prepaneled data is fed into the TCN model for the feature extraction. Finally, the feature is input to the BiLSTM and WANN for yield prediction. BiLSTM can model sequential-based dependencies between data in agriculture, e.g., weather records and soil conditions with robust feature learning. In comparison, WANN is able to optimize the model architecture and shared weights, to learn a light-weight while effective network with low computational cost. Weight parameters are minimized using the LEO algorithm that optimizes the model training and provides higher forecasting accuracy. Through the integration of sensing using the IoT technology, optimized routing and state-of-the-art deep learning techniques, this system provides an accurate and efficient tool for predicting crop yields, aiding sustainable agriculture and more efficient resource use. Fig 1 exhibits the crop yield prediction in IoT adopted with the proposed approach.

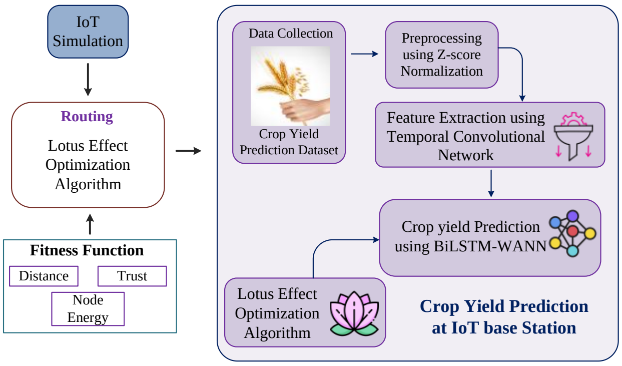

Fig. 1. Crop Yield Prediction in IoT with the Proposed Approach.

3.1 Routing Based on Lotus Effect Optimization Algorithm

In an IoT simulation, routing is carried out to determine the most efficient data transmission paths. The flow of data in the network occurs from the source to the destination through optimal routes selected using the proposed LEO.

Solution Encoding: After routing, solution encoding is performed to analyze the selected paths determined by the LEO approach. It involves mapping the nodes that participate in data transmission and structuring the solution vector accordingly. The chosen paths facilitate efficient data flow through intermediate nodes.

Fitness Function: The optimal solution is also identified by inspecting the set of solutions. The LEO [17] employs a nature-inspired metaheuristic algorithm that utilizes self-cleaning and hydrophobic features of lotus leaves. It integrates 'global and local optimization' to improve the search ability. LEO is selected due to its tradeoff between exploration and exploitation that enhances the solution accuracy. It has the virtues of being robust, flexible, and effective in addressing complicated optimization problems. The fitness of LEO is calculated considering four important parameters such as node energy, trust and distance. The LEO fitness function (Equation (2)) is expressed as follows:

$$Fitness = \frac{1}{3}[N_e + T_u + (1 - M_{dt})] \tag{1}$$

where, N_e denotes the consumed energy, T_u represents the trust level, and M_{dt} denotes the minimum distance.

3.2 Crop Yield Prediction at Base Station

After completing the routing process using the proposed LEO, the BS proceeds with crop yield prediction.

Input Acquisition: In the IoT network simulation, multiple nodes are strategically placed across different locations to facilitate data collection. These nodes gather real-time agricultural data and transmit it to the BS for further processing. The Crop Yield Prediction dataset [18] is a source of data gathering for prediction. The mathematical formulation of this data collection process can be as follows:

$$\boldsymbol{A} = \{\boldsymbol{a_1}, \boldsymbol{a_2}, \ldots, \boldsymbol{a_y}, \ldots, \boldsymbol{a_z}\} \tag{2}$$

where, z represents the total count of data, a_y states y^{th} number data. In the BS, a_y data is dispatched to the preprocessing phase to normalize the data.

Data Preprocessing: The data undergo Z-score normalization [19] or standardization to improve model performance. In order to ensure a mean of 0 and a standard deviation of 1, it converts data by removing the mean and dividing by the standard deviation. This scales the data while preserving its original distribution, making it suitable for deep learning models. The preprocessed output N_d is subjected to the feature extraction.

Feature Extraction: The TCN [20] is a 1-D fully convolutional network that utilizes causal and dilated convolutions to process sequential data while preventing information leakage of the past data. It extracts features using dilated convolution, which expands the receptive field by setting a dilation factor that increases exponentially with depth, ensuring long-range dependencies are captured. It includes capturing long-term dependencies, avoiding gradient vanishing, efficient parallel computation, and handling variable-length sequences due to residual connections and 1×1 convolution for matching input-output dimensions. The dilated convolution operation can be represented as

$$\phi(N_d)(u) = (N_d *_e g)(u) = \sum_{j=1}^{L} g(j) \cdot N_d(u - e \cdot j), u = 1, \ldots, U, \tag{3}$$

where, g denotes the filter and e denotes the dilation factor, L denotes the filter size, u represents the sequence position. Then the extracted feature F_e is fed to the prediction.

Crop Yield Prediction using BiLSTM and WANN: For crop yield prediction, the extracted features are passed into the BiLSTM, which effectively captures temporal dependencies from past and future data points. The output from BiLSTM [21] is then processed by WANN [22], which optimizes the neural architecture without traditional weight training. Together, these models enhance predictive accuracy while maintaining computational efficiency. By processing data both forward and backward, BiLSTM, an advanced Recurrent Neural Network (RNN) architecture, improves on conventional LSTM. It is ideal for time-series analysis since it makes use of both past and future data inside a given sequence. The BiLSTM lies in its bidirectional learning mechanism, which fully utilizes global time-series information, providing superior predictive performance compared to RNN and unidirectional LSTM. The prediction process in BiLSTM involves both forward and reverse computations, represented as

$$\begin{cases} i_u^+ = LSTM^+(y_u, i_{u-1}) \\ i_u^- = LSTM^-(y_u, i_{u+1}) \\ i_u = X^+ i_u^+ + X^- i_u^- + c_z \end{cases} \tag{4}$$

where, i_u^+ and i_u^- denotes the outcome of the layers that forward and backward, $LSTM^+$ and $LSTM^-$ denotes the both operations, X^+ and X^- denotes the weight matrices, c_z denotes the output layer bias term. This enables BiLSTM to deeply learn historical dependencies, improving the accuracy of crop yield prediction. By feeding the BiLSTM output into WANN, the model benefits from both deep sequential learning and efficient neural architecture search, leading to improved predictive accuracy. The predicted output from BiLSTM is then fed into a WANN, which is a neural architecture designed to perform tasks without training weights, relying solely on optimized topologies. It offers efficient, minimal neural architectures that perform well without weight training, reducing computational cost and enabling adaptability across tasks. WANN start with minimal neural network topologies and evaluate performance using common weight values. Networks are ranked based on efficiency, and new topologies are created through mutation and selection, refining architecture over generations. The process continues until the maximum iterations are reached, improving performance without weight optimization. WANN has a self-weight optimizing ability, eliminating the need for traditional weight training, whereas LEO is used to train Bi-LSTM. The BiLSTM-WANN predicted output is denoted as C_p. Crop yield prediction using hybrid BiLSTM WANN is shown in Fig 2.

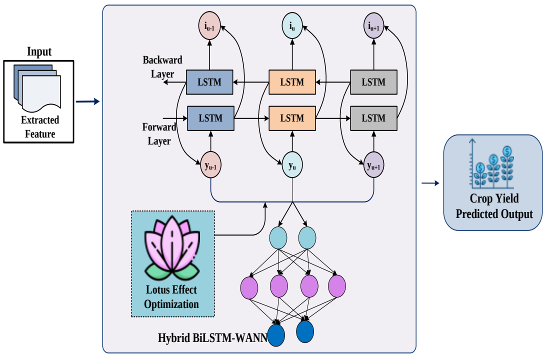

Fig. 2. Crop yield prediction using Hybrid Methodology.

LEO: The weight parameter of the BiLSTM is trained by LEO which minimizes the model prediction error and developes performance. LEO updates the BiLSTM parameters by checking the fitness function that guides the optimization. The prediction error itself determines the fitness function, and the weights are updated iteratively aiming to achieve smaller accuracy error. For more information about LEO, see Section 3.1.2. Such a fitness function can be expressed with:

$$MSE = \frac{1}{h}\sum_{i-1}^{h}[Y_P - C_P] \tag{5}$$

where, Y_P denotes the output that expected and C_P represents the BiLSTM predicted output.

4 Outcome and Analysis

Model evaluation in terms of MAE, MSE and RMSE needs to be compared for accurate prediction of crop yield. The evaluation of algorithm performance shows the proposed method achieves both higher accuracy and faster speed, as compared with the existing method. The error values of the proposed approach are smaller, representing the better prediction and utilization. The system is a PCmachine with OS Windows 10 processor Python 3.12.7 and 2.15 GHz, RAM 1267 GB. The development environment is Visual Studio Code. The model is trained for 20 epochs for best performance.

4.1 Dataset Exploration

The Crop Yield Prediction Dataset aims at prediction of yield of top 10 crops consumed worldwide. It factors in important aspects like the weather conditions (rain, temperature), pesticide usage and historical yield data to make predictions more accurate. This knowledge is important for responding to issues related to food security and climate change. The value of the dataset is in its relevance for agricultural risk management, which is a critical area for data drive-based decision making towards increasing productivity. This data, and these data analysis shall help to create predictive models for sustainable farming practices with the help of machine learning.

4.2 Metrics Performance Evaluation

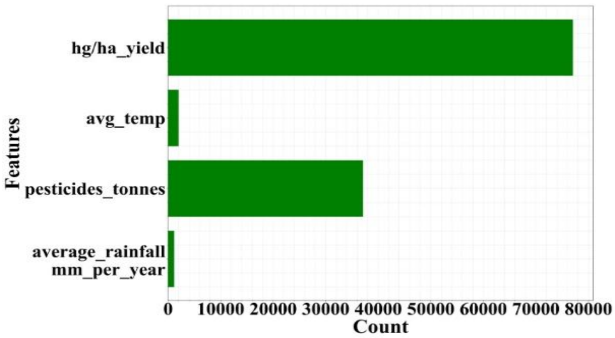

Fig. 3. Dataset Features and Their Count.

Fig 3 presents the features and their counts in the dataset. The yield feature has highest count of 7,534, followed by Pesticides (tonnes) with 3,987 records. Temperature is recorded 245 times, while average rainfall (mm per year) has a count of 123. These features are essential for analyzing and predicting crop yield based on environmental and agricultural factors.

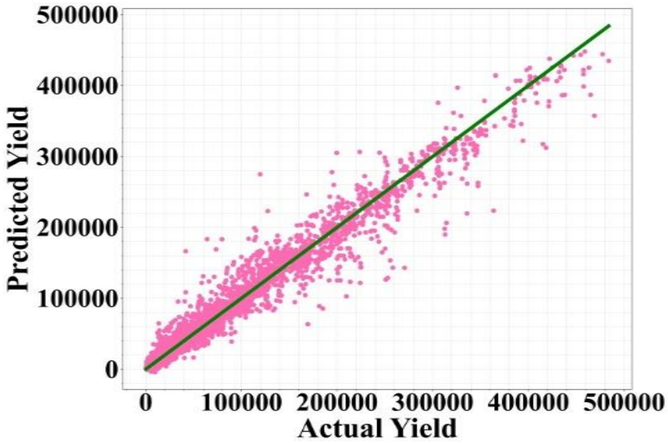

Fig. 4. Regression Analysis of Actual vs. Predicted Crop Yield.

Fig 4 shows the regression of actual yield with predicted yield. The regression data points represent individual predictions, and the line represents the ideal perfect prediction line where predicted values equal actual values. The strong alignment of data points along this line suggests that the model performs well, with minimal deviation, indicating high prediction accuracy.

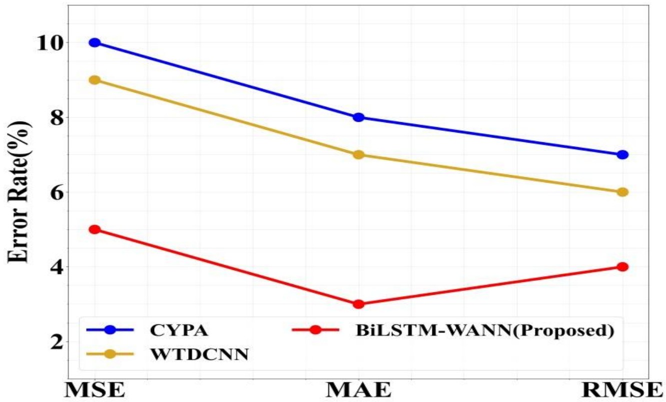

Fig. 5. Comparison of Existing and Proposed Methods for Crop Yield Prediction.

Fig 5 compares crop yield prediction performance metrics for existing and proposed methods. The existing CYPA (Crop Yield Prediction Algorithm) [12] method has an MSE of 10, MAE of 0.0082, and RMSE of 0.0076, while WTDCNN (Weight-Tuned Deep Convolutional Neural Network) [15] shows an MSE of 0.009, MAE of 0.0077, and RMSE of 0.007. The proposed Hybrid BiLSTM-WANN method outperforms both, achieving the lowest error rates with an MSE of 0.005, MAE of 0.003, and RMSE of 0.0048. This demonstrates the superior predictive accuracy of the proposed approach.

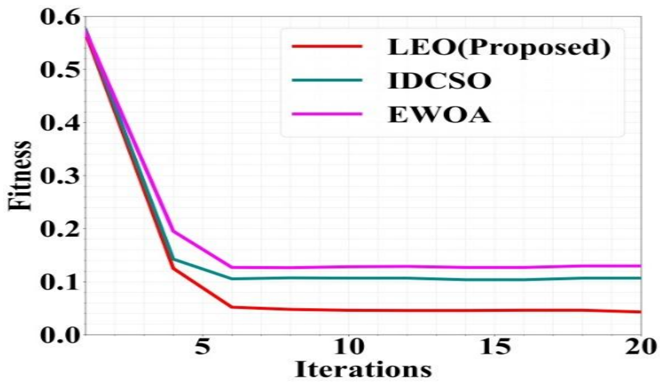

Fig. 6. Fitness Function.

Fig 6 illustrates the fitness function of the optimization process. The existing methods, IDCSO (Improved Distribution-based Chicken Swarm Optimization) [14] and EWOA (Enhanced Whale Optimization Algorithm) [15], achieve fitness values of 0.57 and 0.58, respectively, over 20 epochs, while the proposed LEO method improves from 0.005 to 0.55. This demonstrates that LEO is used to train BiLSTM parameters to enhance prediction accuracy by minimizing errors, and it has the lowest error rate, making it the most effective optimization technique.

4.3 Ablation Study

Table 1 shows the ablation study that evaluates the impact of different components of the proposed method by comparing MAE, MSE, and RMSE. The baseline BiLSTM model has the highest errors, with MAE of 73.23%, MSE of 67.45%, and RMSE of 71.98%, indicating lower performance. Adding WANN improves accuracy, reducing MAE to 47.73%, MSE to 32.57%, and RMSE to 52.96%. Metrics like MAE of 21.23%, MSE of 19.43%, and RMSE of 20.93% show the best performance with the lowest errors when LEO is further integrated.

Table. 1. Ablation Study of the Proposed Method.

Methods	MAE (%)	MSE (%)	RMSE (%)
BiLSTM	73.23	67.45	71.98
BiLSTM-WANN	47.73	32.57	52.96
BiLSTM-WANN-LEO	21.23	19.43	20.93

5 Discussion

Conventional crop yield prediction models are hard to learn complex temporal patterns and a high efficiency, which makes them result inaccurate prediction. This is addressed well in the BiLSTM module, since it can learn the sequential relationship in agricultural sequence data, and extract more robust features. WANN composes a replacement over traditional weight training, lowing computational overhead yet achieving high accuracy. Moreover, the LEO algorithm further optimizes data routing and reduces the weight parameters, thus enhancing the both prediction accuracy and efficiency of the network. In summary, compared with existing methods, the BiLSTM-WANN-LEO method can effectively consider data reliability, computational limitations, and model optimizations, thereby outperforming other models.

6 Conclusion

The hybrid model and the optimization algorithm for crop yield prediction significantly improve utilizing IoT-based data collection, optimized routing, and advanced deep learning. The combination of BiLSTM allows for powerful feature extraction and WANN is used for learning of streamlined neural network for prediction. Experimental results demonstrate that the proposed method achieves superior performance to the existing strategies in terms of both accuracy and computation efficiency. It standardises practices so that resources can be used more efficiently, and we all move quicker toward the goal of sustainable farming, not just the farmers who make fewer mistakes. This would be something that could be addressed in future work to help take the disease detection systems to the next level by adding real time monitoring for early intervention. To broaden its application the system's versatility will be increased by increasing the diversity of species and the scope of environmental factors that can be studied.

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