Enhancing Smart Farming with IoT Sensors Using FRPGW and HALSTM for Accurate Predictions

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Abstract: *This Internet of Things (IoT)-based real-time data collection and analysis system enhances the productivity of agriculture. The use of IoT sensors in monitoring soil conditions optimizes the agricultural methods to resolve problems such as wasteful resource consumption and high operating costs resulting from the lack of accurate, current data and the manual interventions made in the entire process. These data are subjected to pre-processing, including normalization, which normalizes the data scale, and noise filtering to eliminate inaccuracies. Statistical measures are used to calculate the mean, median, skewness, and kurtosis of the data. Feature extraction is applied to derive meaningful insights from the data. Fused Red Piranha Grey Wolf Optimization (FRPGW) algorithm determines the relevant features that can be applied to the accurate models. Crop productivity and drought conditions are predicted by the Hybrid Artificial Long Short-Term Memory (HALSTM) model. It improves resource management, decision-making, and productivity in farms.*

Keywords: *IoT smart farming, agriculture, FRPGW, HALSTM, ANN, LSTM.*

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1. Introduction

Agriculture has been the backbone of human civilization, providing basic resources for survival and economic development. However, traditional farming is confronted with numerous challenges in a world where issues related to climate change, resource scarcity, and growing population pressure all demand more efficient and sustainable agricultural methods [1]. The highest obstacles to optimal farming are the mismanagement of resources, lack of timely observation, and lower predictive accuracy besides having a high cost of operations; these occur because the realistic continuous data is not yet available and it calls for human interventions [4, 5]. The inclusion of Internet of Things (IoT) in farmlands marks an extremely revolutionary step that can beat those problems besides upgrading farm productivity and efficiency in relation to sustainability [12]. Smart IoT-based farming systems use these advanced sensors with connectivity in relation to continually sensing critical parameters for soil moisture and temperature across farms [6, 7]. This real-time data will give farmers unmatched insight into their environment, improved decision-making capabilities, resource optimization, and effective farm management [9].

IoT technology makes resource efficiency in agriculture much better because it uses optimal water. Conventional farming wastes a lot of water; however, IoT sensors can measure the right moisture levels in the soil to create proper irrigation strategies [10, 13]. This optimization does not waste water and prevents problems such as soil erosion and plant stress. In addition, temperature and humidity sensors monitor microclimatic conditions and provide crop protection against the adverse effects of bad weather and disease attacks [15, 16]. Pre-processing ensures accuracy and relevance by standardizing scales for normalized values and eliminating inaccuracies from noise before uploading into databases for use in data-driven analytics [18, 19]. Then it proceeds with extracting subsequent features and computes mean, median, skewness, and kurtosis of data, so as to infer data patterns required for predicting the crop productivity as well as other issues like drought [20, 21].

One of the most important processes that can improve the accuracy of the above-mentioned models of prediction is feature selection. For the purpose of selecting most relevant characteristics, it uses state-of-the-art optimization techniques [22, 23]. For efficient and robust feature selection, the algorithms introduce numerous optimization strategies. The models will obtain higher accuracy and reliability by concentrating on the most relevant elements. This is where the final stage of the intelligent agricultural system comes in place for classification and prediction with advanced predictive models [25, 32]. These models combine various neural network topologies for discovering complex patterns in data. These components, combined in neural networks, give the ability to handle sequential data, long-term dependencies, and learn from history. Integration of all of them offers very powerful equipment in predicting crop yield, anomaly detection, and useful insights in gaining [28]. One important advance in making smart agricultural systems for agriculture is the integration of IoT sensors. Such systems would thus have the capacities to enhance decision-making, resource management, and agricultural productivity, using real-time data, advanced analytics, and predictive modeling [30]. Thus, IoT-based smart farming will be of utmost importance due to the need to have an increase in food production that can only ensure an environment-friendly productive agricultural future.

The following benefits will result from integrating the suggested approach into the farms' present workflow:

1.1. Advantages

- Better decision making: with accurate crop productivity and drought conditions prediction, the farmer can better make informed decisions to allocate his resources rationally.
- Efficiency: manual intervention interference is reduced, thus saving time and labor with predictive automation.
- Optimized use of resources: better predictions ensure that waste is minimized through proper irrigation and fertilizer application.
- Long-term sustainability: better data-driven insights result in practices which lead to sustainable farming and yield over the long term.

1.2. Disadvantages

- Data dependence: this model requires strong, coherent, and reliable data from IoT sensors that may not always be available or credible in a rural environment.
- Complexity: introducing such a model into traditional workflows could also require a lot of training on farmers' part.
- Cost of implementation: initial setup costs for IoT sensors, data infrastructure, and model deployment may be high.

1.3. Study Limitations

While the proposed Fused Red Piranha Grey Wolf Optimization (FRPGW) model demonstrates superior performance in weed detection using the Indian states dataset on agricultural crop yield, several limitations should be acknowledged to provide context for the scope and applicability of the findings:

- Geographical scope: the dataset primarily covers Indian states from 1997 to 2020. Thus, the model's performance and conclusions may not generalize well to other countries or regions with different climatic conditions, soil types, agricultural practices, or crop management systems.
- Crop diversity: although multiple crops are included in the dataset, the model has not been explicitly tested across a broad variety of crop types or weed species outside those represented. Therefore, the adaptability of the model to other crop-weed ecosystems remains uncertain.
- Temporal constraints: the data spans over two decades but does not account for potential recent changes in farming technologies or environmental shifts post-2020, which might affect model accuracy if applied in current or future scenarios without retraining.
- Environmental and agronomic variables: the model relies on available agronomic and environmental features such as rainfall, fertilizer use, and pesticide application, but may not capture other influential factors like soil microbiome dynamics or pest pressures, limiting comprehensive generalization.
- Computational constraints: the implementation and validation were performed on a specific computational platform and using a particular feature set, which may impact replicability and performance under different hardware or data conditions.

Addressing these limitations in future work through the inclusion of more diverse datasets, real-time data incorporation, and cross-regional validations would enhance the robustness and generalizability of the model.

The following represents this paper's contributions,

- This work presents an IoT-based smart farming system that boosts agricultural efficiency with real-time data, improving resource management and prediction accuracy.
- This work uses IoT sensors for real-time data collection and employs pre-processing techniques like normalization and noise filtering to ensure accuracy.
- This work leverages FRPGW optimization algorithm for feature selection, effectively identifying the most relevant features to improve the accuracy of predictive models.
- This work applies Hybrid Artificial Long Short-Term Memory (HALSTM) model for precise prediction and classification, combining Artificial Neural Network (ANN) with Long Short-Term Memory (LSTM) to capture complex patterns, ultimately optimizing resource management and boosting farm productivity and sustainability.

This paper is structured as follows for the remainder of it. In section 2, a list of relevant works and an explanation of the issue are provided. The suggested methodology is shown and described in section 3. Section 4 presents the findings and discussion, and section 5 presents the conclusion.

2. Literature Review

Alzubi and Galyna [2] used Artificial Intelligent (AI) and IoT technologies in farming alongside advanced computer science applications. Recently, there’s been a shift towards effectively utilizing these technologies. Agriculture, essential for millennia, is now integrating IoT for ecosystem monitoring and high-quality production. However, Smart Sustainable Agriculture (SSA) encounters challenges in IoT/AI deployment, data sharing, interoperability, and managing vast data.

In the work of Kethineni and Gera [14], this attention mechanism is integrated into a Gated Recurrent Unit (GRU) neural network, hence resulting in an Attention-based GRU (AGRU). This mechanism will enable the model to concentrate on the most relevant parts of the input sequence, thereby allowing it to identify and highlight important temporal patterns in the data. The AGRU model will improve the detection of anomalies or intrusions for IoT-based farming systems, thanks to the fact that different weights are given to attention at different time steps or features. In this way, the network will be able to select the most relevant information when it tries to decide what to do in order to determine anomalies. This results in better general performance and a higher accuracy of the intrusion detection process.

Attention mechanism is not discussed in the work by Mahajan *et al*. [17], but it has been focused on how to improve the efficiency of IoT in smart farming using the Cross-Layer Internet of Things (CL-IoT) protocol. The proposed protocol enhances energy efficiency, computational efficiency, and Quality of Service (QoS) using CL clustering and optimal cluster head selection. Delays and energy consumption are reduced in this system with the aid of a nature-inspired algorithm for routing. The attention in this context can be viewed as the ability of the protocol to concentrate its efforts on those key parameters through the selection of optimal cluster heads and paths to route with priority to the most important elements of the system, that is, energy efficiency and computational efficiency, such that maximum final performance is achieved.

Faid *et al*. [8] presented a flexible IoT framework for AI-powered smart farming. This low-cost, hybrid multi-agent system offers real-time data and AI-based forecasts while continuously monitoring agricultural metrics. It has quick deployment and maintenance, a user-friendly online interface, and strong communication.

Patrizi *et al*. [24] developed a Wireless Sensor Network (WSN) using low-cost, low-power Photvoltaic (PV)-powered sensor nodes to collect environmental and soil data. They tackled soil moisture sensor challenges by proposing an LSTM-based deep learning approach for a virtual soil moisture sensor, validated through performance comparisons with other learning-based methods.

Bouali *et al.* [3] proposed an integral Smart Agriculture (SA) solution addressing water scarcity and environmental impact due to unmonitored control and extensive fossil fuel use in irrigation. Along with the rapid population growth and increased food demand, optimal water-table and energy usage are essential for sustainable agriculture. The economical SA solution emphasizes intelligent irrigation, renewable energy integration, and smart water metering.

Gebresenbet *et al.* [11] presented a concept for fully integrating digital technologies to improve future smart agricultural systems. The concept integrates smart data collection tools, AI analysis, edge/cloud computing, Blockchain, and data security systems. This approach promises increased data value, productivity, and innovative farm models, supporting the sector’s competitiveness and digital transformation. Future research directions are also outlined.

Sengupta *et al*. [26] proposed IoT-enhanced device FarmFox, designed to merge traditional farming with advanced technology for sustainable agriculture. FarmFox is excellent at remote control, actual analysis for soil health monitoring, and real-time data collecting. Utilizing Arduino-based hardware, it offers a cost-effective alternative to existing devices. The incorporation of turbidity and pH parameters into FarmFox has proven successful in monitoring soil health. Its real-life implementation is anticipated to provide a budget-friendly, smart solution for advancing sustainable agriculture.

Sharma *et al*. [27] highlighted innovations such as high-throughput phenotyping, remote sensing, and AgroBots for automating harvesting, sorting, and weed detection, reducing costs and environmental impact. Advanced image segmentation aids accurate plant and fruit detection, while Differential Global Positioning System (DGPS) and sensing tools monitor soil and crop health. Case studies like Pacman and Pantheon showcase transformative impacts. Future advancements, including 5G/6G integration, must address scalability, real-time decision-making, and data privacy challenges.

Vasudevan and Ekambaram [31] proposed a Hybrid Air Quality Prediction (HYAQP) system combining k-means clustering with the Sine Cosine Algorithm (SCA). The integrated approach optimizes cluster centroids to classify air quality into three categories good, moderate, and poor enabling timely interventions and effective pollution management.

2.1. Problem Statement

A major problem in traditional farming practices is inefficient resource management, limited real-time monitoring, poor predictive accuracy, and high operational costs. These problems arise mainly from the lack of accurate, continuous data and the dependence on manual intervention processes. Inefficient use of water leads to wastage and a possibility of soil erosion, whereas the lack of monitoring of environmental conditions such as temperature and humidity can cause damage due to diseases or unfavourable weather conditions. Moreover, the inability to accurately predict crop productivity and issues such as drought conditions exacerbates the inefficiencies. These problems thus hinder optimization in agricultural practice, making it difficult to reach sustainable and productive farming outcomes.

3. Proposed Methodology

An IoT-based smart farming system collects, monitors, and analyses data in real time for efficient agriculture. Traditional farming faces a lot of issues in resource management, insufficient real-time monitoring, low accuracy in prediction, and high operating costs. The main reasons for these issues are the dependency on manual intervention approaches and also the lack of accurate and continuous data. An IoT-based smart farming solution is proposed herein to solve the aforementioned issues in a multi-phase manner.

3.1. Pre-Processing

3.1.1. Normalization

The data collected requires pre-processing to ensure it is suitable for analysis. One crucial stage in this process is normalization, which standardizes the scale of the collected data, allowing for consistent comparisons across features measured on different scales (see Figure 1 for the overall proposed architecture).

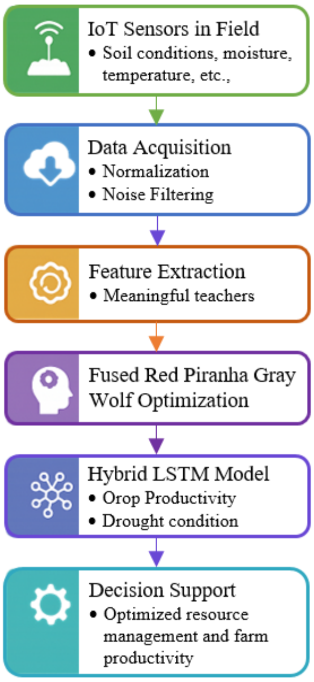


Figure 1. Overall proposed architecture.

It thus allows each feature to have equal contributions through standardizing the values measured in different scales into a common one. This also helps prevent any particular feature from overwhelmingly influencing the model, thereby ensuring data integrity. In this context, data standardization was critical, as the input originated from multiple sensors using different units. Standardizing it enables meaningful and accurate comparisons based on factual values.

3.1.2. Noise Filtering

Noise filtering helps in improving data quality by removing those data points, which are either not accurate or contain errors in the dataset. It therefore involves finding and removal of noise and outliers that may distort the study and result in invalid conclusions. In IoT-based smart farming, such aberrations may be witnessed in data coming from sensors due to either environmental conditions or sensor malfunction. Noise filtering ensures that the dataset going through further analysis is clean and reliable, hence improving the accuracy of predictive models and general decision-making processes.

3.2. Feature Extraction

The next step is feature extraction; whereby useful information is extracted from the pre-processed data. The following statistical metrics are involved:

3.2.1. Mean

The mean, or average, describes central tendency by sum total divided by count, but it is skewed by outliers, so it’s always important to consider other measures like the median and mode for a complete analysis. The mean of a set of data is denoted by $\bar{x}$ and is given using Equation (1).

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (1)$$

3.2.2. Median

The median is the middle value of a sorted dataset, which is insensitive to outliers. For odd-numbered observations, it’s the value at position (n+1)/2. For even-numbered datasets, it’s the average of the two central values, based on ascending or descending order.

3.2.3. Skewness

Skewness is a metric used to quantify how asymmetrically values are distributed within a collection. The following is the formula to determine *skewness*:

$$Skewness = \frac{3 \times (mean - median)}{standard\ deviation} \quad (2)$$

Equation (2) multiplies the mean-median difference by three and divides by the standard deviation.

3.2.4. Kurtosis

One can compute kurtosis, a measure of a distribution’s tailedness, by dividing the fourth-order moment by the population’s raised-to-fourth power standard deviation.

It reflects how often outliers occur, with excess kurtosis indicating tailedness relative to a normal distribution. The formula for calculating kurtosis (K) is given as per Equation (3).

$$k=\frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\sigma^4} \tag{3}$$

3.3. Features Election

By identifying the most pertinent elements of the dataset, it is crucial to increase the prediction models' accuracy.

3.3.1. FRPGW

Grey wolves follow a strict social hierarchy in their packs. Alphas are the dominant pair that leads in decision-making. Betas assist and possibly become alphas. Gamma submits to all and serve as scapegoats, crucial for pack harmony. Subordinates include scouts, sentinels, elders, hunters, and caretakers, each with specific roles. Group hunting is when they track, chase, and attack their prey collaboratively. This hierarchical structure ensures effective pack functioning and exemplifies the importance of cooperation and discipline in wolf societies. Red Piranha Optimization (RPO) is inspired from the hunting behavior of red piranha fish and has three phases: Encircling, searching, and attacking. With "prey encircling" and "frenzy" signals to make a synchronized frenzy for capturing the prey, scouts guide the swarm.

3.3.1.1. Prey Searching

A protected flock of red piranha fish is formed in the search phase, with weaker individuals in the centre and more powerful scouts on the outside. Scouts keep an eye on the environment in search of prey, guiding the group to surround that prey. The group then follows an attack-then-escape strategy. Integrating the hunting behavior of grey wolves improves the algorithm by combining the searching technique of the piranha with coordinated wolf tactics. In nature, wolves hunt in groups where alpha, beta, and delta wolves lead the way and the rest of the pack follows them. Similarly, in RPO, scouts are guiding the search in order to enhance exploration, which also helps avoid getting stuck in a local optimum. Combination of the above strategies gives a more robust optimization algorithm that results in better solutions. According to the proposed Equations (4) to (6), RPO makes advantage of this collective intelligence to improve its capacity for exploration, enabling it to move around the search space more effectively and stay out of local optima.

$$\overrightarrow{dpm_\alpha}=\left|\vec{c}_1\vec{X}_\alpha-\overrightarrow{Xpm}\right|,\ \overrightarrow{dpm_\beta}=\left|\vec{c}_2\vec{X}_\beta-\overrightarrow{Xpm}\right|,\overrightarrow{dpm_\gamma}=\left|\vec{c}_3\vec{X}_\gamma-\overrightarrow{Xpm}\right| \tag{4}$$

$$\overrightarrow{Xpm_1}=\vec{X}_\alpha-\vec{a}_1\cdot\overrightarrow{dpm_{\alpha,}}\overrightarrow{Xpm_2}=\vec{X}_\beta-\vec{a}_2\cdot\overrightarrow{dpm_\beta},\overrightarrow{Xpm_3}=\vec{X}_\gamma-\vec{a}_3\cdot\overrightarrow{dpm_\gamma} \tag{5}$$

$$\overrightarrow{Xpm}(t+1)=\frac{\overrightarrow{Xpm_1}+\overrightarrow{Xpm_2}+\overrightarrow{Xpm_3}}{3} \tag{6}$$

3.3.1.2. Prey Encircling

The search region is randomly searched by scouts in RPO, and when a prey is found, alpha fish emit a Prey Encircling Signal (PES) to initiate encirclement. A logarithmic spiral is employed during the encircling phase to guide the movement in the direction of the prey. In order to improve RPO performance, position update will be dependent on the distance from the predicted prey and optimize exploitation utilizing Equations (7) to (10).

$$\overrightarrow{Xprey}(t)=\frac{1}{f}\begin{pmatrix}\sum_{i=1}^{f}x_{1i}\\ \sum_{i=1}^{f}x_{2i}\\ \cdots\\ \sum_{i=1}^{f}x_{ui}\end{pmatrix} \tag{7}$$

$$\vec{d}=\left|\overrightarrow{Xprey}(t)-\overrightarrow{Xpm}(t)\right| \tag{8}$$

$$\overrightarrow{Xpm}(t+1)=\vec{d}\cdot e^{bls}\cos(2\pi ls)+\overrightarrow{Xprey}(t) \tag{9}$$

$$ls=1-\frac{2t}{z_{enc}} \tag{10}$$

3.3.1.3. Prey Attacking

When the encircling phase is completed, the victim is fully surrounded. The herd now struggles to reach the prey in the assault phase initiated by alpha fish. Search agents' positions are updated according to distance and the estimated position of prey.

$$\overrightarrow{dpm}=\left|\vec{c}\overrightarrow{Xprey}(t)-\overrightarrow{Xpm}(t)\right| \tag{11}$$

$$\overrightarrow{Xpm}(t+1)=\overrightarrow{Xprey}(t)-\vec{a}\cdot\overrightarrow{dpm} \tag{12}$$

$$\vec{a}=2\vec{g}\cdot\overrightarrow{rv_1}-\vec{g} \tag{13}$$

$$\vec{c}=2\cdot\overrightarrow{rv_2} \tag{14}$$

$$g=2-t*\frac{2}{z_{att}} \tag{15}$$

3.4. Prediction and Classification

In this research work, there are prediction and classification as the major elements for analyzing and predicting agricultural metrics. This includes the following method.

3.4.1. HALSTM

This is the HALSTM model applied in this research work for prediction and classification tasks. The proposed HALSTM model has combined strengths in both the ANN and LSTM networks, in capturing complex patterns within the data. The ANN is very effective at modeling complex nonlinear relationships, while the LSTM is good at handling sequential data and thus making it suitable for time-series prediction. By fusing these two models, HALSTM can manage IoT data complexities for an accurate prediction. The model significantly improves the prediction accuracy and stability of the smart farming system, thus guaranteeing better resource management and decision-making.

- **Input Layer**

This layer receives raw data or features and passes it to hidden layers for computation, and it contains one neuron for every feature. No computation occurs in this layer.

- **Hidden Layers**

Hidden layers are those that perform core computations in a neural network and process inputs with weights, activation functions, and outputs depending on the complexity, as calculated using Equation (16).

$$a_{ij} = f\left(\sum_{k=1}^{n_{i-1}} w_{ik} a_{ik} + b_{ij}\right) \quad (16)$$

The output of each neuron in a hidden layer is calculated using a weighted sum of inputs and a bias term.

- **Output Layer**

The neural network's final output is determined by the output layer, with neurons tailored to the problem type.

LSTM-based Recurrent Neural Networks (RNNs) excel at capturing long-term dependencies in sequences, making them ideal for time-series and NLP tasks due to their memory blocks.

- Input layer: receives sequential-data input.
- Hidden layer: contains LSTM units responsible for processing and retaining information.
- Output layer: creates the final product using the information that has been processed.

LSTM replaces the basic units of regular RNNs with memory cells, which allow them to retain information over long sequences. LSTM units have three main gates: input gate, forget gate, and output gate.

- Input gate: regulates how fresh data enters the memory cell.
- Forget gate: selects the data from the memory cell to remove.
- Output gate: adjusts the output according to the input's previous state and present value.

The activation of each LSTM unit at time l_t is calculated using Equation (17):

$$l_t = \sigma(wm_{i,l} \cdot x_t + wm_{h,l} \cdot l_{t-1} + bi) \quad (17)$$

Where, l_t and l_{t-1} represent the activation at time respectively, σ is a non-linear activation function, $wm_{i,l}$ is the input-hidden weight matrix, $wm_{h,l}$ is the hidden-hidden weight matrix, bi is the hidden bias vector, and x_t is the input at time t. LSTM networks excel at capturing long-term dependencies in sequential data. They mitigate the problem of gradient vanishing, allowing for more effective learning over longer sequences.

4. Result and Discussion

4.1. Experimental Setup

The proposed model is implemented using the Python platform. After that, it is compared to other models that are already in use, such Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and RPO. The efficacy of the suggested model in weed identification may be assessed by contrasting performance measures including accuracy, precision, F1-score, and recall, which will reveal why it is better than existing techniques.

The proposed FRPGW model was implemented using Python with TensorFlow and Keras libraries. The model combines feature-rich preprocessing with an optimized deep learning framework for weed detection. The training process and architecture configuration are detailed below:

4.1.1. Model Architecture

- Input layer: accepts time-series input windows of size 10 (i.e., data from 10 consecutive time steps).
- LSTM layers: two stacked LSTM layers with 128 and 64 units, respectively, used to capture long-term dependencies in the temporal data.
- Dense layers: two fully connected layers with 64 and 32 neurons, followed by a final output layer.

4.1.2. Activation Functions

- LSTM layers: tanh (default)
- Dense layers: ReLU
- Output layer: sigmoid (for binary classification)
- Dropout: dropout layers with a rate of 0.3 were applied after each LSTM layer to prevent overfitting.

4.1.3. Training Configuration

- Optimizer: Adam optimizer with an initial learning rate of 0.001.
- Loss function: binary Cross-Entropy.
- Epochs: the model was trained for 100 epochs.
- Batch size: 64.
- Early stopping: implemented with a patience of 10 to halt training if no improvement in validation loss is observed.
- Windowing technique: a sliding time-series window of size 10 with a stride of 1 was applied to transform sequential data into input samples.
- Evaluation metrics: accuracy, precision, recall, and F1-score were used to evaluate and compare model performance.

4.2. Data Collection

Indian states dataset on agricultural crop yield [29]. Data on agricultural yields for several Indian states from 1997 to 2020 are included in this collection. In addition to key agronomic variables including area under cultivation, production volume, yearly rainfall, fertilizer and pesticide use, and crop type, year, season, and state, it includes data for several crops. Crop year, crop, state, season, area, annual rainfall, production, fertilizer, pesticides, and yield are the ten characteristics that make up the data set. Researchers may examine how various agricultural and environmental practices have caused differences in crop yields by using this data set to assess agriculture for yield prediction. Therefore, it may be even more beneficial to create machine learning models and comprehend how India's agricultural production vary between regions and time periods.

4.3. Proposed and Existing Model Overall Performance Analysis

A detailed comparison of the performance of the proposed FRPGW model with the RPO, GWO, and PSO models is represented in Table 1.

Table 1. Proposed and existing model performance analysis.

Methods	Accuracy	Recall	Precision	F1-score
RPO	0.80	0.80	0.86	0.84
GWO	0.81	0.82	0.85	0.81
PSO	0.83	0.81	0.87	0.82
Proposed FRPGW	0.94	0.90	0.95	0.87

The comparison is mainly based on four leading performance measures: Accuracy, recall, precision, and F1-score.

- The number of precise forecasts, encompassing true positives and true negatives, as a percentage of all instances examined is known as accuracy. It is in the accuracy of the proposed FRPGW model, with a higher value of 0.94, surpassing RPO's 0.80, GWO's 0.81, and PSO's 0.83, showing the better ability to classify instances in the right classes and thus high improvement in generalization ability.
- Precision is the ratio of correctly identified positive instances to the total positive instances predicted. The proposed FRPGW model outperforms with a precision of 0.95 compared to RPO's 0.86, GWO's 0.85, and PSO's 0.87. Higher the precision rate, better the FRPGW model is at reducing false positive rates.
- Recall is the percentage of true positives that were predicted correctly. In this regard, by having a recall value equal to 0.90, FRPGW has better performance compared to the RPO, GWO, and PSO models. This improvement shows the greater ability of the FRPGW model in recognizing actual positive instances and decreasing false negatives.
- The F1-score provides the harmonic mean for the precision and recall trade-off. Our FRPGW model provides an F1-score of 0.87, which is only slightly less than the obtained precision and recall and higher compared to RPO with a 0.84, GWO with a 0.81, and PSO with a 0.82. It shows that the model performs very well in accurately predicting the number of genuine positives, hence reducing the number of false positives and false negatives.

The proposed FRPGW model has considerably raised performance on all metrics evaluated and hence proved effective and reliable in the task of weed detection. From the detailed analysis above, this model is more effective in delivering more accurate and dependable results compared to the approaches.

4.4. Graphical Representation

Figure 2 shows the comparison between the proposed model and the already existing models, namely, GWO, RPO, and PSO, based on four metrics:

a) Accuracy: the proposed model outperforms others with a score of 0.94.
b) Precision: the proposed model has the highest precision at 0.95.
c) Recall: the proposed model leads with a score of 0.90.
d) F1-score: the proposed model maintains a balanced performance with a score of 0.87.

4.5. Justification for Model Selection

The choice of baseline models (PSO, GWO, RPO) was motivated by their widespread use and proven effectiveness in optimization-based classification and feature selection tasks in agricultural and image-processing domains. These metaheuristic algorithms are known for their balance between exploration and exploitation, yet each has limitations:

1. PSO may converge prematurely in complex, high-dimensional search spaces.
2. GWO often struggles with local optima due to limited diversity in later iterations.
3. RPO, although more recent, lacks adaptive guidance for dynamic input conditions like crop variability and environmental features.

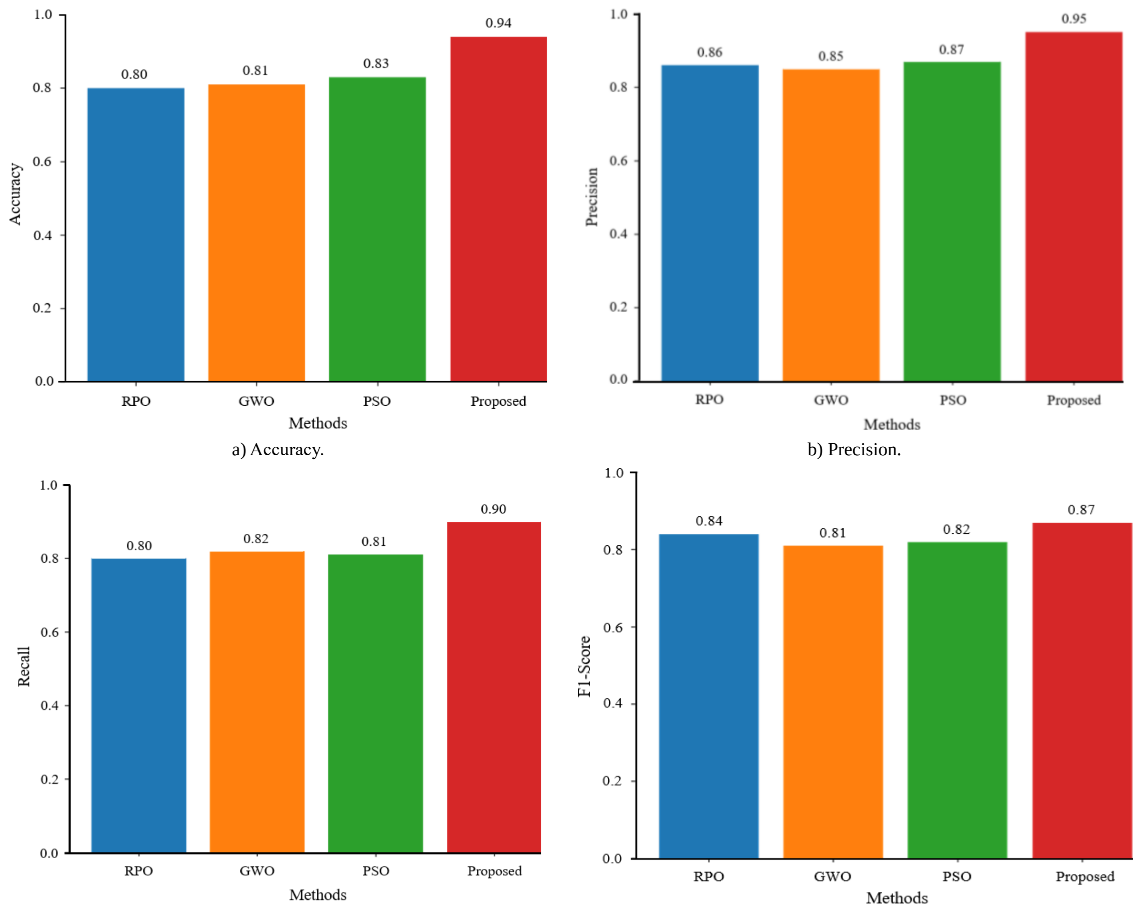
To overcome these challenges, the FRPGW model was proposed. This hybrid leverages the adaptive intelligence of RPO and the strong leadership hierarchy of GWO to enhance search efficiency and convergence accuracy, especially for identifying subtle patterns in agricultural datasets like weed presence.

4.6. Statistical Significance of Improvements

While performance metrics (accuracy: 0.94, precision: 0.95, recall: 0.90, F1-score: 0.87) indicate the superiority of the FRPGW model, statistical significance testing is essential to confirm that these improvements are not due to random variation.

The higher precision (0.95) and recall (0.90) of the FRPGW model imply that it effectively balances minimizing false positives and false negatives-a critical requirement in weed detection, where both under- and over-identification can harm yield and resource allocation. The F1-score of 0.87 confirms this balance.

Moreover, the consistent performance across multiple metrics and visual graphs in Figure 2 supports the model's generalization ability across different subsets of the dataset.



a) Accuracy. b) Precision. c) Recall. d) F1-Score.

Figure 2. Graphical representation of existing and proposed model.

5. Conclusions

By continuously gathering, monitoring, and analyzing data, an IoT based smart farming system used IoT technology to increase agricultural efficiency. Due to the lack of accurate, continuous data and reliance on manual procedures, traditional farming faced problems with resource management, real-time monitoring, prediction accuracy, and high operating expenses. The proposed system employs a multi-phase approach, using IoT sensors for real-time data on soil pH, temperature, humidity, light, and moisture. After that, the data underwent pre-processing, which involved noise reduction to get rid of errors and normalization to normalize scales. In order to extract useful insights, feature extraction involves computing statistical metrics including mean, median, skewness, and kurtosis. The most pertinent characteristics were found using the FRPGW optimization approach for feature selection in order to improve the prediction model's accuracy. In order to detect intricate patterns and provide precise predictions of agricultural yield and drought conditions, the HALSTM model which combines ANN and LSTM was employed for prediction and classification. This comprehensive strategy improved decision-making, improved resource management, and raised agricultural output and sustainability.

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Data Availability Statement

All the data is collected from the simulation reports of the software and tools used by the authors. Authors are working on implementing the same using real world data with appropriate permissions.

Author Contributions

All authors significantly contributed to the development of the described tool, and are currently actively involved in it. The first draft of the manuscript was written by Corresponding Author and co-author improved on previous versions of the manuscript. All authors read and approved the final manuscript.

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