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Smart Agriculture with CNN-LLOA Optimization: An IoT-Based Approach for Climate Change Adaptation and Environmental Protection

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Abstract

Indian agriculture, the backbone of the country's economy, faces significant challenges due to climate change and crop diseases. Soil productivity is highly dependent on water availability and seasonal variations in India. In addition, environmental changes in neighboring regions also contribute to global warming. Climate variability intensifies the outbreaks of diseases, threatening food security. This research aims to enhance precision farming in India by proposing a smart agricultural framework using IoT (Internet of Things) sensors, advanced routing algorithms, machine learning (ML), and reinforcement learning (RL). With the help of environmental and crop-related data like soil moisture, temperature and humidity the framework can resourcefully utilize resources, improve yield, protect the climate, and ensure resiliency to climate change. Information such as temperature and crop health is measured by strategically positioned IoT sensors across farmlands and sent through the Bee Guided Routing Protocol (BGRP) and Energy Efficient Routing Protocol (EERP) for proper management of data flow. Farmers and agricultural specialists can make informed decisions due to the processing, storing, and computing capabilities offered by Cloud technologies, which facilitate easy access to data. The proposed hybrid Convolutional Neural Network–Lotus Leaf Optimization Algorithm (CNN-LLOA) refines and processes the dataset to improve prediction accuracy. Anomalies like insect and disease infestations, anomalies, and agricultural yield are predicted alongside the detection of crop conditions.

Keywords: Smart Agriculture, IoT, Deep learning, BGRP and EERP protocols, CNN-LLOA optimization.

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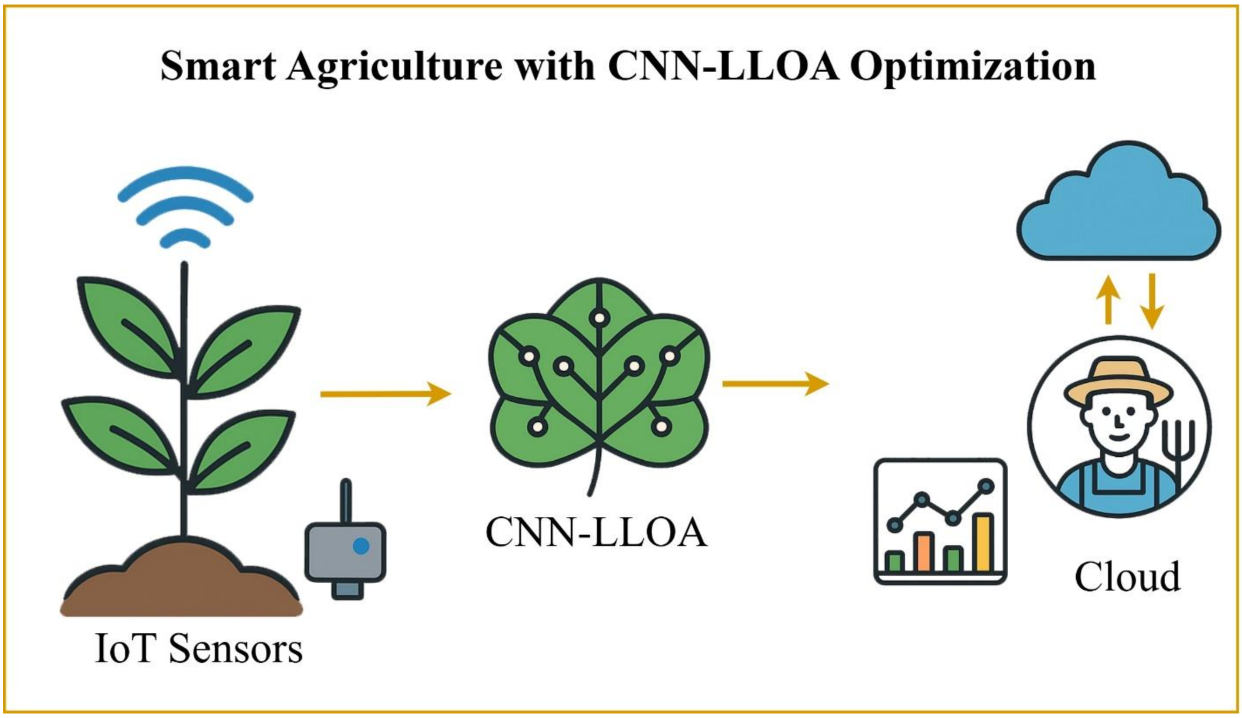
Graphical abstract



1. Introduction

Agriculture plays a vital role in the economic development of many countries, particularly in developing regions. However, climate change, water scarcity, soil degradation, and pest infestations continue to pose major challenges to agricultural productivity. Other developing nations facing similar climatic and agricultural challenges can also adopt the proposed model. The framework can adapt to various environmental and geographical conditions because it integrates cloud computing, machine learning algorithms, and Internet of Things (IoT)-based sensing. With minor modifications, the model can be applied in countries across Asia, Africa, and Latin America that experience issues such as water scarcity, irregular rainfall, soil degradation, and pest infestations. The CNN-LLOA's adaptability and the IoT sensor network's modular design enable modification according to regional crop varieties, climate zones, and soil properties. Additionally, the framework is economically feasible for low-resource areas due to the utilization of inexpensive sensors and energy-efficient routing protocols like BGRP and EERP. Agriculture is the cornerstone of many nations, including India. Water shortages often occur depending on location and seasonal conditions (Dilip Charaan & Therasa, 2022). Farmers traditionally evaluate soil conditions and make crop decisions based on experience and assumptions. However, climate conditions, humidity, and water levels were often not considered adequately, which negatively affected farmers (Naresh & Munaswamy, 2019). India's agricultural land area is projected to reach over 130 million hectares by 2024.This is for the production of food grains. If current population growth rates continue, the World Bank projects that more than half of all food will need to be produced before 2050. However, current climate change will not support such huge agricultural production. Consequently, advanced farming is becoming more and more necessary (Reddy *et al.*, 2020).

Every society's social structure, economy, and environment are significantly impacted by this crucial industry. Agriculture's development in food and cattle production has enabled significantly more human population increase than hunting and gathering could (Deepa *et al.*, 2021). Rain-fed agriculture, irrigation systems, and groundwater irrigation are all at risk due to the growing demand for water, which reduces agricultural productivity in areas where irrigation is required (Patil *et al.*, 2023).

Many agricultural difficulties are exacerbated by global climate change (Paudel *et al.*, 2023). Due to water constraint brought on by droughts, heat waves, and floods, crop productivity frequently declines when temperatures rise and weather patterns shift (Kim & Lee, 2023). Thus, crop failures that happen concurrently in several locations may become more likely as a result of climate change. A conceptual framework called climate-smart agriculture (CSA) provides possible answers to these complex issues (Borrelli, 2023). Implementing measures that enhance adaptation, reduces greenhouse gas emissions, and maintains national food security can lead to sustainability in agriculture (Raihan, Ridwan, & Rahman, 2024). Farmers learn about pH level, temperature, and soil with smart farming techniques.

The proposed initiative aims to enhance precision agriculture in India by developing a smart farming framework using IoT sensors, advanced routing protocols, and AI algorithms. Aims include an effective monitoring of agricultural and environmental metrics – soil moisture, temperature and humidity; accurate forecasting of crop condition, pest activity and yield; and resource optimization for a sustainable agriculture. The study is motivated by the need to resolve issues that affect food and productivity like diseases, drought, and climate change. To encourage climate-resilient and high-yield agricultural practices, the work is directed towards collecting actual field data using IoT, energy-efficient feed transmission using BGRP and EERP, cloud-based processing to support decision making, using the PLC scheme and semi-hybrid CNN-LLOA model to enhance real-time datasets and prediction.

The third agricultural revolution, precision agriculture is geared towards solving the sustainability problem and the rise in the expected consumption of food (Sanka, Booba, & Boopathi, 2023). IoT technology is used to monitor and control factors such as sunlight, soil moisture content, temperature, and humidity to create an automated agricultural system. The farm has different sensor nodes placed in different places. The microcontroller can make use of cameras, sensors, and Wi-Fi to perform the above-mentioned purposes and these parameters can be modified with any remote device or online service (Suma *et al.*, 2017).

According to Sekaran *et al.*, (2020), the verification of the thought has been around for some time, however, it is increasingly being undertaken as a result of recent developments of hardware technology. Through IoT, physical gadgets can communicate with the internet to detect, collect, store and prepare data (Senthil Kumar *et al.*, 2021). IoT provides data for monitoring agricultural environments through wireless sensor networks (WSNs). It decides on the data of the plants. The smart farming system's monitoring capabilities can be enhanced and the network's scalability increased by adding more sensor nodes to the current WSN (Koshariya *et al.*, 2023). The prediction engine sends information to the notification server, which then forecasts the outcomes (Gupta & Nahar, 2022).

All data including sensor-collected and recorded information, job history, fertilizer distribution, camera images of the growth process, and environmental data is stored in the cloud (Channe, Kothari, & Kadam, 2018). The intersection of cloud computing and IoT is essential. The combination of the Internet of Things' data-gathering potential with cloud computing's extensive storage, processing, and service capabilities creates a true network that connects people, objects, and the items themselves (Patil *et al.*, 2012).

The capability of blockchain technology can boost trust in food labeling and standards. With farmers as its primary consumers, its main purpose is to shorten the certification procedure schedule (Hasan *et al.*, 2024). The AGRU neural network model is used to identify irregularities in data that protects privacy. By adding an attention mechanism, an AGRU expands on the capabilities of the conventional GRU model.

In a new ensemble-based machine learning classification method that consists of two prediction levels, the level-1 meta classifier (Random Forest) receives input features from K-Nearest Neighbors (KNN), logistic regression (LR), support vector machines (SVM), classification and regression trees (CART), and additional classifiers. The level-0 prediction detects different categories of crops. Various sectors, including smart cities, transportation, healthcare, and agriculture, have found applications for SDNs (Syed, 2024). Based on application requirements, SDN allows for dynamic management of network resources and traffic (Masood *et al.*, 2023).

Preserving and improving the results (Kethineni & Gera, 2023), is also aided by the advancement of sophisticated agricultural technology, such as artificial intelligence, machine learning, and deep learning. Using machine learning (ML), drones and tractors boost production, while supply chain optimization helps the farmer align planting with consumer demand. In addition to the integration of farm management systems, which can provide an important understanding of the potential for reduction of climate change impact, machine learning (ML) further supports climate adaptation above the ground through data analysis.

Various machine learning techniques were used to predict different natural disasters under climate change. For instance, Random Forest (RF) was used to predict extreme temperatures, Support Vector Machines (SVM) to predict tsunamis, Convolutional Neural Networks (CNN) to predict cyclones, and Long Short-Term Memory (LSTM) networks to predict earthquakes. The models were used to develop a robust meta-algorithm that was optimized for real-time data collection and analysis in the Internet of Things (IoT). The accuracy of the meta-algorithm increased by 5% as compared to the regular models like Ensemble Decision Tree model and the Logistic Discriminant model (Babu *et al.* (2025)). Utilizing the l-Biruni Earth Radius Optimization approach for RS imagery with deep transfer learning-based scene image classification (AERODTL-SIC). The different types of sceneries were identified by the AERODTL-SIC method that extracted characteristics from RS photos using a deep convolutional neural network-based SqueezeNet algorithm. The AERODTL-SIC method uses a deep autoencoder neural network for scene image classification. With the help of the AERO model, the DAENN model's parameters were precisely chosen, improving classification performance (Sivasubramanian *et al.* (2025)).

IoT, cloud computing, AI, and machine learning have all significantly advanced precision agriculture; yet, a number of drawbacks and problems still exist in the models that are currently in use. Despite their heavy reliance on sensor networks and data collecting, many existing systems frequently suffer from restricted scalability across broad or diversified farmlands, energy limits, and intermittent or unreliable connectivity. Furthermore, while though AI models like ensemble classifiers, AGRU, and neural networks increase prediction accuracy, they can be computationally demanding, needing sophisticated infrastructure and a lot of computing power, which not all farmers may be able to afford. Existing frameworks are less robust in real-world situations because they frequently lack the flexibility to adjust to different climatic zones, crop types, and unanticipated environmental abnormalities.

The following are the key phases of the suggested approach, for further Contribution:

- The research introduces a smart farming architecture integrating IoT sensors, cloud computing, and ML/RL algorithms to improve precision farming in India.
- Utilization of BGRP and EERP ensures effective and energy-efficient data transmission from IoT sensors across farmlands. Strategic placement of IoT sensors enables continuous monitoring of soil moisture, temperature and humidity supporting proactive decision-making.
- A proposed hybrid CNN-LLOA optimization model enhances accuracy in anomaly detection, crop condition monitoring, and yield prediction.
- The framework contributes to climate change mitigation and sustainable farming practices by optimizing resource use and predicting threats like crop diseases and pest infestations.

The following section will discuss the proposed system's structure: section 1 describes introduction. In Section 2, the suggested system's definition is discussed. Performance values are computed and the results are examined in Section 3. The conclusion and future work are explained in Section 4.

2. Materials and Methods

Figure 1 shows the smart agriculture system using IoT, cloud computing, and advanced machine learning algorithms for precision farming. The main objective of the system is to collect environmental parameters such as soil moisture, temperature, and humidity using sensors. Smart sensing protocols like EERP and BGRP enable the transfer of these parameters to an IoT gateway. The data is then sent to a cloud platform for storage and processing, by the IoT gateway. The acquired information is evaluated with a CNN-LLOA optimization model.

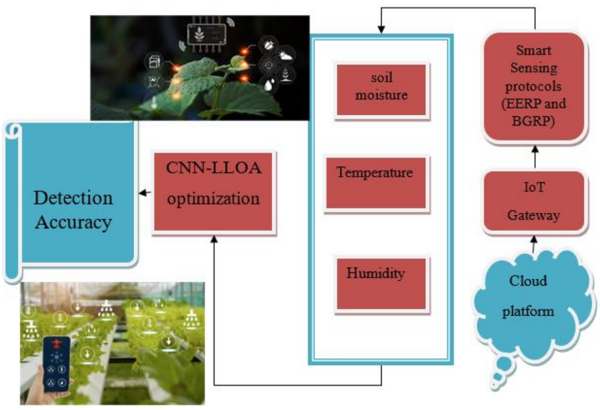


Figure 1. Proposed block diagram for an IoT-based smart agriculture system.

In this setting, CNN refers to a Convolutional Neural Network, and LLOA is an optimization technique used to improve model performance. The findings of the study improve the detection accuracy of plant diseases or growth conditions. Graphic messages generated by the real-time monitoring interface demonstrate the usability of the smart farming system in the field.

2.1. *Cloud Computing*

Cloud computing generally refers to the offering of technology services over the Internet. These technology services may include, database, networking storage solution, processing etc. The ability to only pay for used resources, rather than investing in the construction and operation of physical servers and data centres, can provide cloud customers with a major advantage. The combination of cloud computing and the Internet of Things enables real-time data collection, analysis, and decision-making, thereby creating the novel field of "smart agriculture" in farming.

2.2. *Smart Agriculture with IoT*

Figure 2 provides an overview of the elements involved in IoT-based smart agriculture. The Internet of Things (IoT) is a revolutionary development that represents the future of computing and communications, emerging from swift progress in various critical fields, including wireless sensors and nanotechnology. A simple, inexpensive, and unobtrusive means of identifying items to connect everyday objects and devices with extensive databases, networks, and the broader internet. Only then can item data be collected and processed. It is facilitated by radiofrequency identification (RFID). Secondly, sensor technologies will help in data collection by detecting changes in an object's physical state.

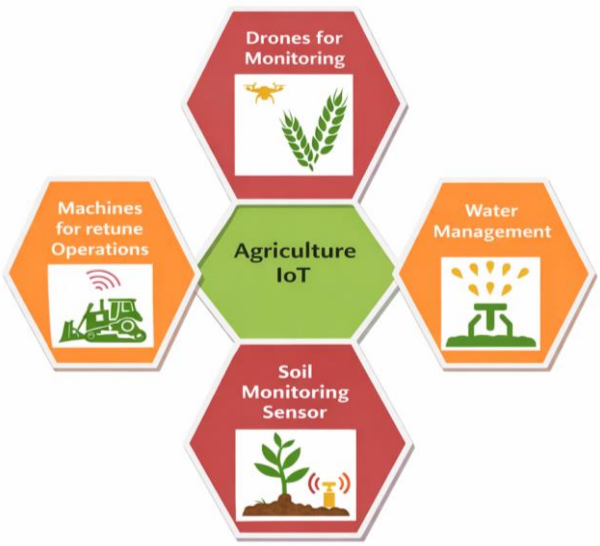


Figure 2. Overview of an agriculture IoT.

Embedded intelligence in the items themselves can help the network by giving its edges the ability to process information. Finally, downsizing and nanotechnology developments will enable ever-tinier objects to interact and communicate. An Internet of Things that connects the world's items sensually and intelligently will be the result of these advancements.

2.3. *IOT-based Smart Agriculture Monitoring in WSN*

Datang Mobile introduces the Wisdom Agriculture system, an IoT solution for agriculture. **Figure 3** depicts an operational IoT-based smart agriculture sensor monitoring system. It depicts a lush green agricultural landscape complete with sensor nodes that communicate data via WSN, as depicted by the signal icons radiating from the crops. A smartphone in the foreground shows a smart farming application interface with real-time environmental metrics like sunshine intensity, temperature, humidity, soil moisture, and plant health status. This configuration illustrates how farmers can employ IoT technology for remote monitoring and management of agricultural conditions, allowing them to make well-informed choices regarding crop health, fertilization, and irrigation. The background of the image, featuring mountains and nature, highlights the technology's value in rural and semi-remote agricultural regions.

Figure 3. IOT-driven smart agriculture oversight.

2.4. *IoT Device and Sensors*

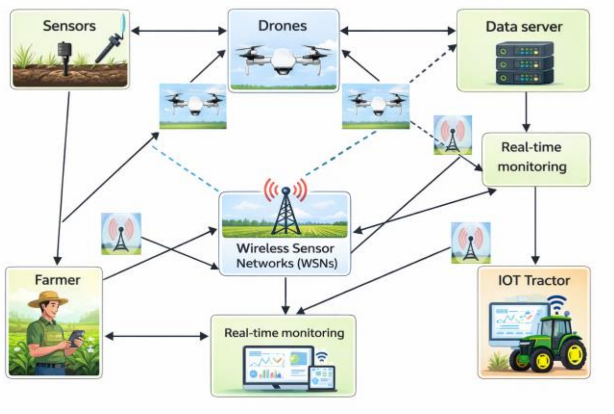


Figure 4. IOT-based smart agriculture monitoring system.

Sensors, cameras, display units, microcontrollers, and network elements like switches and routers come in a variety of forms. Actuators are used to condition the sensor characteristics according to the results of the prediction tasks (Abunadi *et al.*, 2022). The central processing unit is main job is to transfer data between parts that can be used to process Internet of Things devices. An IoT-based irrigation solution, for example, may accelerate watering by granting it as soon as it detects soil moisture data from WSNs, conserving water and assuring healthy plants. IoT device monitoring and control for smart agriculture is shown in **Figure 4**.

2.5. *EERP and BGRP Protocol in WSN*

EERP and other energy-efficient routing protocols are vital for the long-term operation of field-deployed devices, especially in remote, low-energy agricultural areas. The BGRP routing protocol draws its inspiration from the foraging of bees, which is known to be effective. It is useful to WSNs due to its efficient and adaptive routing schemes. Bee-Guided Routing Protocol (BGRP) and Event-Driven Energy-Efficient Routing Protocol (EERP) combined to offer a hybrid solution with improved functionality of Wireless Sensor Networks (WSN) in smart agriculture. By including the advantages of both strategies, the hybrid protocol provides the data transport reliability and energy efficiency.

BGRP and EERP work together to provide better access for IoT devices to cloud. It guarantees consistent connectivity while consuming less energy. The EERP distributes the energy load among sensor nodes to avoid premature battery depletion while the BGRP chooses the most convenient data paths based on parameters like signal strength, distance, reliability, etc. Network traffic is overall lessened by leveraging the data aggregation and compression techniques at intermediate nodes to limit replicated transmissions. In intelligent agriculture scenarios, such a hybrid scheme guarantees fast, low-latency communication to the cloud while ensuring the robustness and energy efficiency of the IoT network.

The proposed smart agriculture framework integrates BGRP and energy-efficient EERP to provide reliable, efficient and sustainable data communication between IoT sensor nodes and the central cloud server. The Internet of Things (IoT) sensors placed around the farms constantly monitor data at sensor network layer. The data tracked includes soil moisture, temperature, humidity, and crop health indicators.

The hybrid model incorporates several key features:

- Event-Driven Data Collection: Agricultural factors, such as crop health and temperature, are continuously monitored by the sensors. Data packets will only be transmitted when they contain important information to reduce useless transmissions and save energy.
- Adaptive Path Selection: Once the protocol detects an event, it applies BGRP-like methods to select the most appropriate routes to the base station. Those routes are optimized based on network congestion, node energy levels, transmission history, and distance from the data sources.
- Data Aggregation and Compression: Intermediate nodes have the ability to increase energy efficiency and reduce the volume of data sent to the base station by using data compression techniques which allow for the integration of data from numerous sensors prior to transmission.
- Benefits of Smart Agriculture.

The overall hybrid approach may apply in smart agriculture scenarios for better results and increased efficiency. For agriculture, it ensures coherent supply and significantly increases energy efficiency. Through the algorithm, the growers can give preference to unattended critical conditions and respond on time. The algorithm will assist in agricultural monitoring. By using effective load balancing the costs of network maintenance will be reduced and its operating life will be increased. The protocol is reliable and adaptable to changes in dynamic agriculture scenarios that ensures performance and success.

In the agricultural sector, IoT technology depends significantly on a variety of sensors. The system consists of three layers: the sensor layer, transport layer, and application layer. They serve the following functions:

2.5.1. Soil Moisture

In **Figures 5(a) and 5(b)**, the soil moisture sensor assesses the volumetric water content in the soil and delivers an output indicating the moisture level of the soil. A current is allowed to flow through the soil from one terminal sensor to another in order to ascertain its moisture content. The current value is determined by the moisture content of the soil. The amount of stream that passes through the soil depends on its moisture content. Determining the amount of water available close to the plant is made easier by measuring moisture.

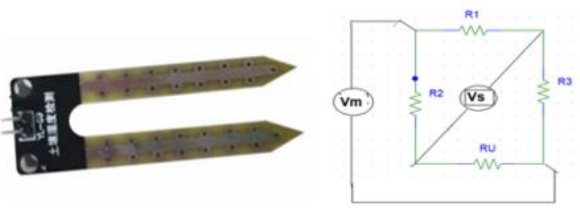


Figure 5 (a) soil moisture sensor (b) and its equivalent circuit.

Resistance is a measure of soil moisture content. The following formula is used to measure the unknown soil resistance that is a component of the Wheatstone Bridge:

$$R_u = \frac{\dfrac{R_3}{R_1+R_3} + \dfrac{V_m}{V_s}}{1 - \left(\dfrac{R_3}{R_1+R_3} + \dfrac{V_m}{V_s}\right)} R_2 \quad (1)$$

Where R_u represents the unknown resistance of the soil moisture sensor, R_1, R_2, R_3, denote the known bridge resistances, V_s represents the supply voltage, and V_m denotes the measured output voltage.

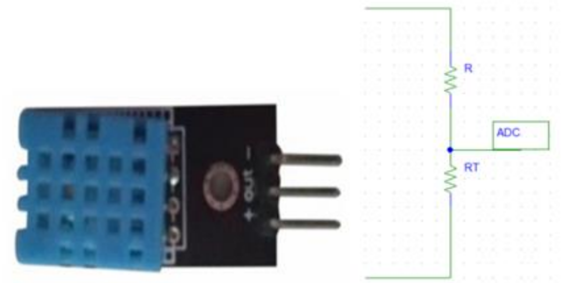


Figure 6. (a) DHT11 temperature and humidity sensor and (b) its equivalent circuit.

2.5.2. Sensor forSe HSeumidity and Temperature

The DTH11 sensor, which monitors temperature and humidity, is illustrated in **Figures 6(a) and 6(b)**. Monitoring the temperature and humidity in the plant's vicinity is advantageous. The thermistor's resistance in the sensor varies with temperature changes. By measuring the temperature, the farmer can determine the best location for the plant to grow. To determine the air's moisture content, the DTH11 uses two electrodes. The electrodes of the capacitive RH sensor are divided by a polymer comb. Capacitance is temperature-dependent. The voltage across the capacitor changes due to capacitance variations, mirroring the air's live humidity at a given temperature.

Water vapour and other gases are found in air. An ideal gas is used to mimic dry air. A long way from the dome water pressure is dry air. The ratio of water vapour (-ω.) to saturated water vapour (-s.) is known as the relative humidity. At the saturation point, the water condenses. The following formula can be used to determine relative humidity:

$$RH = \left(\frac{\rho_\omega}{\rho_s}\right) \times 100\% \quad (2)$$

Where RH represents the relative humidity expressed as a percentage, ρ_ω denotes the density of water vapour in the air, and ρ_s represents the density of saturated water vapour at the same temperature.

2.5.3. pH Sensor

Soil pH measurement is carried out using the liquid ph0-14, shown in **Figure 7**. It ascertains which types of substances are found in the soil. To measure the activity of hydrogen ions in soil, the pH sensor (Prakosa *et al.*, 2022) is utilized. For plants to thrive, the average pH level of the soil should range from 6.5 to 7.5. Different species of plants need varying pH levels in order to flourish. The soil's pH level can be affected by the type of soil used for plant growth, the quantity of fertiliser applied, and the amount of water used. In order to conduct this experiment, the cactus plant requires a pH level of 5 to 7. Before measuring the pH of the soil, a buffer solution is used to calibrate the pH sensor.

Figure 7. pH Sensor

The following expression converts this temperature-measured potential to pH:

$$E(T) = E^{\circ}T - 0.1984T\ pH \quad (3)$$

Where $E(T)$ represents the measured electrode potential, $E^{\circ}T$ denotes the standard electrode potential, T represents the absolute temperature in Kelvin, and pH denotes the hydrogen ion concentration level of the solution.

2.5.4. Vibration Sensor

If there is any wind that could harm the plants, the farmer is notified by the vibration sensor (801S). Vibrations are converted to resistance changes using this sensor. Even when employing micro shock sensing, this sensor can provide information on vibration in real time. When no vibration occurs, the sensor emits a low voltage. When the sensor detects vibration, the square shows in the output. Extreme winds can inflict significant harm to plants. The farmer can use this activity to determine whether the plant is being moved, chopped down, or disturbed by a human, bug, or reptile. Because the sensor would transmit data to the cloud in the event that something happened to the plant, this method would assist farmers in being more watchful over the safety of their plants. If the vibration sensor detects any harm, a red LED will light up. To determine whether any harm has been done to the plant, turn the screw on the vibration sensor to a specific range. **Figures 8(a) and 8(b)** show the vibration sensors utilized here.

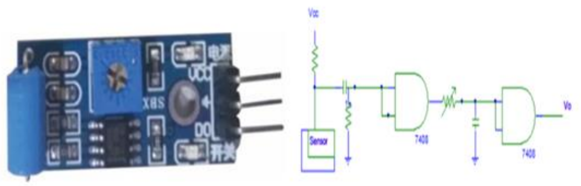


Figure 8. (a) Vibration Sensor, b) Vibration Sensor Equivalent Circuit

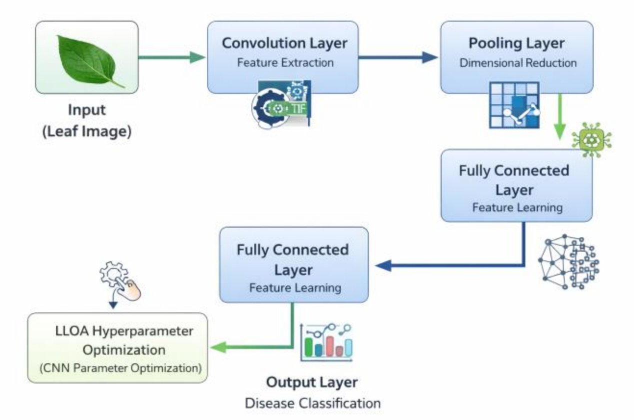


Figure 9. Hybrid CNN- LLOA classifier overview diagram

2.6. *Hybrid Approach CNN- LLOA Classifier*

Numerous studies have looked into using bio-inspired algorithms, such as LLOA, to improve classification task performance in agricultural applications, particularly in the identification of plant diseases. The LLOA is an optimization method that draws inspiration from nature by modeling its operations after the characteristics and actions of lotus leaves. When applied to damaged leaf classification, LLOA can increase the efficacy and accuracy of machine learning models. **Figure 9** showcases the overview of the proposed approach of the Hybrid CNN-LLOA classifier. The functioning of LLOA and its use in the classification of sick leaves are explained in detail below.

- Lotus leaves have a special surface structure that allows them to reject water and dirt. This is known as the "self-cleaning mechanism." During the optimization process, ineffective solutions can be filtered out using optimization algorithms that take advantage of this characteristic.
- Water droplets can roll off lotus leaves, bringing detritus with them. This feature can encourage the investigation of the solution space, where "droplets" stand in for possible solutions that are traveling in the direction of better areas determined by performance indicators.

The architecture of the proposed approach integrates deep learning capabilities with optimization techniques for the classification of diseased leaves, as shown in **Figure 9**. The design of the proposed hybrid CNN-LLOA architecture, along with its key functionalities and interactions, is described below. The architecture begins with an input layer that receives leaf images for further processing.

2.6.1. Convolutional Neural Network (CNN) as the primary

The convolutional layers apply filters to pull various information from the input images. More complex features relevant to the diseased classes are captured in the deeper layers as the early layers capture simple features like edges and textures. Usually, a convolutional layer would be followed by a ReLU activation function and may be prevented by Batch Normalisation. Max-pooling layers reduce memory usage and computation in a neural network with no significant loss of accuracy. It works by down-sampling the input representation, reducing its dimensionality and retaining only the most essential features. The final flattened representations are processed by fully connected (dense) layers following some convolutional and pooling layers. The output classes (healthy vs. various ill categories) are mapped to the learned features via these layers. The output layer uses a SoftMax activation function to produce class probabilities and is made up of neurons that correspond to the classes (healthy, disease type 1, disease type 2, etc).

2.6.2. LLOA optimizer

Feature/Hyperparameter Optimization Layer – (Candidate Solutions): LLOA initializes a collection of candidate solutions that mirror various CNN setups, such as: - Convolutional layer filter size or number choices. Batch sizes, dropout rates, and learning rates.

A predetermined fitness function (such as accuracy on a validation set) is used to assess each candidate configuration's classification performance after it has been trained on the dataset. Only the most promising candidate configurations are kept for additional assessment and investigation after poor-performing candidate configurations are filtered away in the Self-Cleaning Mechanism.

The algorithm navigates the hyperparameter space, enabling the finding of configurations that could result in higher classification accuracy is Exploration and Exploitation. Candidates that possess advantageous traits are urged to sway other candidates in their vicinity, simulating the flow of droplets on lotus leaves. Until a stopping condition (like a maximum number of iterations or fitness convergence) is met, iterative optimisation is continued.

2.6.3. Training and Validation Process

The CNN is trained using the training dataset and the optimal candidate configuration (optimized hyperparameters) chosen from LLOA during the first training phase. During training, backpropagation is used to minimize a loss function, usually categorical cross-entropy for multi-class classification tasks.

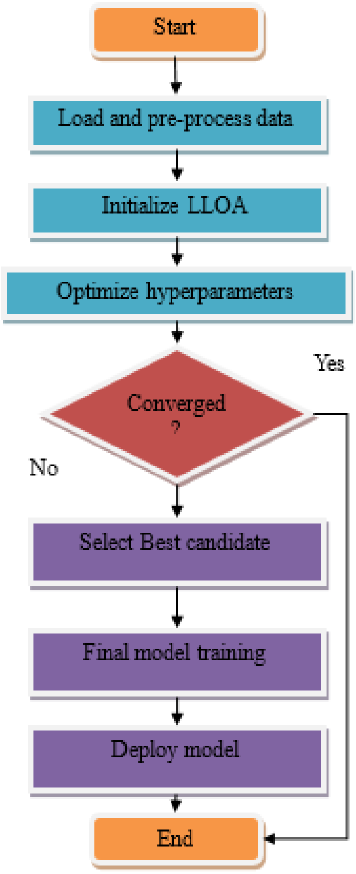


Figure 10. Flowchart for Hybrid CNN-LLOA classifier

For the purpose of this research and analysis, the CNN-LLOA was selected as it combines the optimization capabilities of the self-adaptive LLOA with the feature extraction capabilities of Convolutional Neural Networks (CNNs) to handle complex agricultural datasets. In the field of deep learning, CNN refers to Convolutional Neural Network which is likely to be extensively used to identify spatial and visual patterns in images. Yet, other issues such as overfitting, difficulty in tuning parameters and local minima traps plague CNNs alone. Taking a cue from lotus leaves' adaptive water-repelling and natural-self-cleaning characteristics, the LLOA component addresses these drawbacks and enables the CNN model to facilitate an effective global search, quicker convergence and ideal weight tuning. Compared with other hybrid optimization strategies, CNN-LLOA generates more accurate solutions in changing situations at a lower computational cost with greater stability. The bio-inspired flexibility of smart farming applications boosts their prediction accuracy, energy efficiency and real-time performance thanks to an improved robustness to noisy and non-linear agricultural information.

Algorithm 1: Hybrid CNN-LLOA classifier

```
function leaf classification(dataset_path)
  // step 1: load and preprocess data
  load dataset from dataset_path; preprocess dataset (resize, normalize)
  // step 2: initialize lloa
  set population_size = n; initialize candidates with random hyperparameters
  // step 3: optimize hyperparameters
  while not converged do
    for each candidate in candidates do
      cnn_model = initialize_cnn(candidate); train cnn_model on training data
      candidate.fitness = evaluate(cnn_model, validation data)
    end for
    // selection of top performers
    sort candidates by fitness descending
    top_candidates = select top_k from candidates
    // generate new candidates
    candidates = top_candidates + mutate(top_candidates)
  end while
  // step 4: final model training
best_candidate = select best candidate; final_cnn_model = initialize_cnn(best_candidate)
  train final_cnn_model on entire dataset
  // step 5: validate and test
  test_accuracy = evaluate(final_cnn_model, test dataset)
  // step 6: deploy model
  deploy(final_cnn_model)
function mutate(top_candidates)
  new_candidates = []
  for each candidate in top_candidates do
    new_candidate = candidate.copy()
    modify random hyperparameter in new_candidate
    append new_candidate to new_candidates
  end for
  return new_candidates
end function
function evaluate(model, dataset)
  predictions = model.predict(dataset)
  accuracy = calculate accuracy from predictions and true labels
  return accuracy
end function
```

The CNN's performance should be verified on a different validation dataset in order to fine-tune and improve the model. Once successfully trained and validated, the model is deployed for classifying new leaf images, providing real-time predictions on whether leaves are healthy or diseased and performance data were obtained.

The Hybrid CNN-LLOA classifier's flowchart, which depicts the step-by-step process of model construction and optimization, is depicted in the **Figure 10**. Preprocessing, which involves cleaning, resizing, and normalizing raw agricultural data, comes first. After that, a population of random hyperparameter candidates is created by initializing the Lotus Leaf Optimization Algorithm (LLOA). Hyperparameter optimization is the next step in the process, when each candidate is assessed according to model performance. In the event that the optimization has not converged, fresh candidates are created and revaluated by a decision node. The best candidate is chosen for final model training using the optimum CNN configuration after convergence is reached. The cycle from data collection to implementation is then completed when the trained model is put into practice for precision agriculture.

2.7. *Performance Measures*

The confusion matrix is one of the key indicators in the deep learning network classification process. The remaining values are provided by the Confusion matrix.

$$\frac{TP}{TP+TN+FP+FN} \tag{4}$$

$$\frac{TP}{TP+TN} \tag{5}$$

$$\frac{TP}{TP+FP} \tag{6}$$

$$\frac{TP}{TP+FN} \tag{7}$$

Where, true positive cases TP to the total number of predictions, including true positives, true negatives TN, false positives FP, and false negatives FN. The proposed smart agricultural framework's accuracy is improved by a number of coordinated tactics. First, by placing IoT sensors in strategic locations, measurement errors are decreased and thorough, high-quality data gathering for important crop and environmental factors is guaranteed. Second, by reducing data loss or corruption, the use of sophisticated routing protocols like BGRP and EERP guarantees dependable and energy-efficient delivery of sensor data. Third, the model's prediction power is enhanced by the hybrid CNN-LLOA, which processes and improves the dataset by combining metaheuristic optimization with deep learning feature extraction.

3. Results and Discussion

The dataset used in this study consists of approximately 3,200 plant leaf images and environmental sensor records collected from different agricultural regions. The dataset was divided into 70% training data and 30% testing data to evaluate the model performance. All experiments were implemented using MATLAB R2023a with the Deep Learning Toolbox. The experiments were conducted on a computer system with Intel Core i7 processor, 16 GB RAM, and Windows operating system. This configuration enabled efficient training and evaluation of the proposed CNN-LLOA model.

Real-time field data collected from different agricultural regions in India were used in MATLAB to visualize the eight field characteristics. The dataset was used for training and validation in this study. In order to continuously monitor environmental and crop-related factors like soil moisture, temperature, humidity, pH level, nutrient content, and leaf wetness, IoT-enabled sensors were strategically placed throughout farmlands. To increase the variety and resilience of the training samples, this real-time data was combined with satellite imagery and historical meteorological data. To guarantee that the suggested hybrid CNN-LLOA could learn efficiently from real field conditions, enabling precise detection, prediction, and decision-making in precision agriculture, the gathered datasets were subsequently pre-processed and separated into training and validation subsets. The final structure that best reflects the model performance according to the evaluated criteria is shown in **Table 1**.

Table 1. CNN-LLOA hyperparameter configuration.

Parameter	Value
Normalization layers	1–2
Epochs	22
Kernel size	3 × 3
Number of nodes per layer	100
Optimizer	RMSProp
Dropout rate	0.3 – 0.5
Learning rate drop factor	0.1
Activation function	ReLU
Convolution layers	1–3
Pooling type	Max pooling / Average pooling
Batch size	9

3.1. *Sensor result using EERP and BGRP Protocols*

The irrigation data for several sensors, including moisture, temperature, and humidity. When it hits the threshold level, the device sends an appropriate action to the fieldwork robot. **Figure 8** depicts the irrigation of raw data information using moisture, temperature, and humidity sensor outputs. This continuous graph depicts well-performed device activities during the feedback processing period.

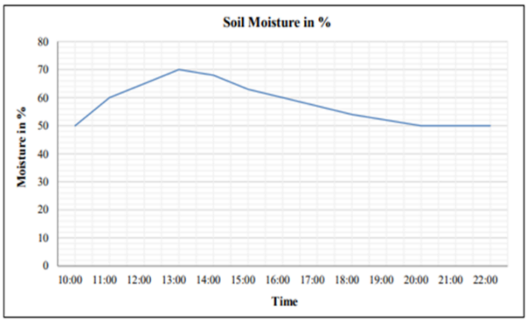


Figure 11. Result from soil moisture sensor data using EERP and BGRP Protocol.

Water is provided every hour from 10 a.m. to 1 p.m. As the plant is given more water, the total amount of water in the soil rises; this can be tracked. At 10 a.m., the value under examination is 50%, and at 1 p.m., it is 70%. A graph illustrating the time-related changes in moisture content is shown in **Figure 11**. One can induce trembling in the plant by placing a high-speed fan at a short distance from it and turning it on. monitoring the vibrations of the system and adjusting the speed of the fan.

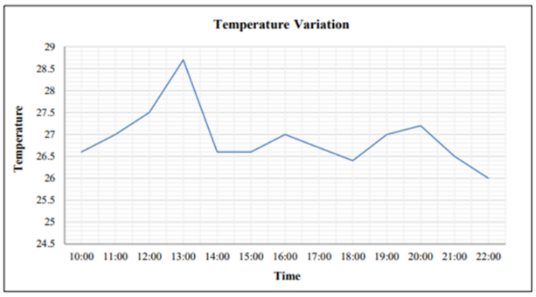


Figure 12. Result from temperature sensor data using EERP and BGRP Protocol.

The range of temperatures is 26 to 28.7 degrees Celsius. Around one in the afternoon, the day's highest temperature is reached. **Figure 12** illustrates this variation through charting.

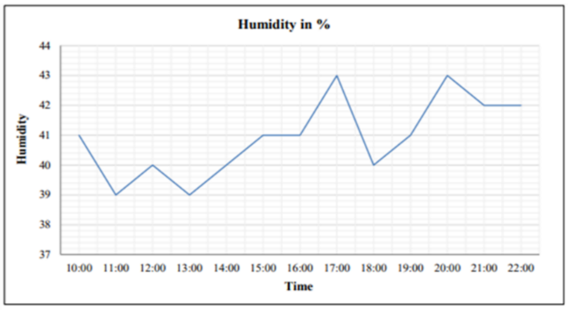


Figure 13. Result from Humidity sensor data using EERP and BGRP Protocol.

In the vicinity of the plant, humidity levels hit their nadir at about 7 p.m. and their zenith at 10 a.m. **Figure 13** illustrates the development of humidity levels.

3.2. *Histogram Representation*

An enclosed image will have an improved contrast and detail visibility because the pixel intensity is more evenly distributed. The image's histograms demonstrate that, in comparison to the original images, the equalized images feature a greater range of pixel intensities. It is now simpler to discern between various characteristics and objects in the image because the darker portions have been brightened and the lighter portions have been darkened. The result is mentioned in **Figure 14**.

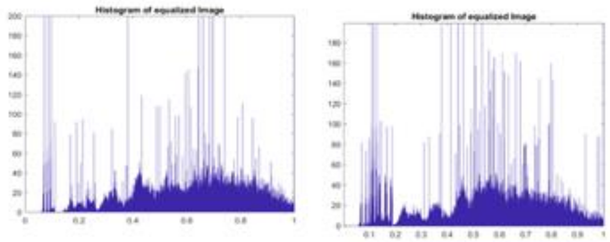


Figure 14. Histogram of equalizes images.

3.3. *Confusion Matrix*

In classification problems, a confusion matrix is a performance-measuring tool frequently used to assess a model's accuracy. A table known as the confusion matrix shows each class's accurate and incorrect predictions, providing an overview of how well a classification system performed as mentioned in **Figure 15**.

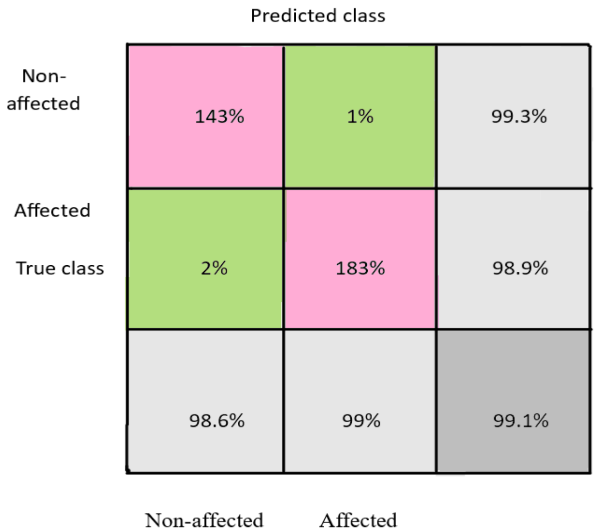


Figure 15. Confusion Matrix.

Table 2 and 3 shows the results of fine-tuning methods like Xception, RegNetx002, MobilenetV3small, a comparison of training accuracy in proposed CNN-LLOA.

Figure 16 shows that the Plant disease detection comparative study of the performances in several years.

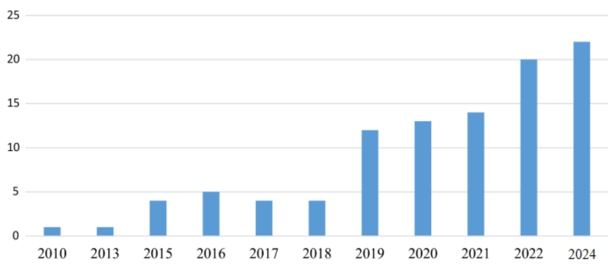


Figure 16. Plant disease detection comparative study of the performances in several years.

Table 2. Comparison of performance matrices.

Model	Precision	Recall	F1 score
Xception (Meena *et al.*, 2024)	0.100	0.96	0.98
RegNetx002 (Chauhan *et al.*, 2022)	0.99	0.93	0.96
MobilenetV3small (Gao *et al.*, 2023)	0.99	0.94	0.90
Proposed (CNN-LLOA)	0.99	0.982	0.984

Table 3. Accuracy comparison.

Methods	Accuracy level
RegNetx002 (Chauhan *et al.*, 2022)	98.6
MobilenetV3small (Gao *et al.*, 2023)	98.89
Proposed method (CNN-LLOA)	99.1

4. Conclusion

The proposed smart agricultural framework efficiently incorporates IoT sensors, modern routing protocols like BGRP and EERP, and AI techniques such as ML and RL to dramatically improve precision farming in India. The hybrid CNN-LLOA optimization model achieves excellent accuracy (99.1%), allowing the system to precisely monitor and predict crop conditions, pest infestations, and yield. Using real-time environmental data and cloud-based analytics, the framework provides farmers with actionable insights, supporting sustainable agriculture and climate resilience. Future work will focus on improving the model's adaptability to different climate zones and crop varieties in India. Integration with real-time satellite imaging, edge computing for reduced latency, and blockchain for secure data exchange are all possible upgrades.

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