

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

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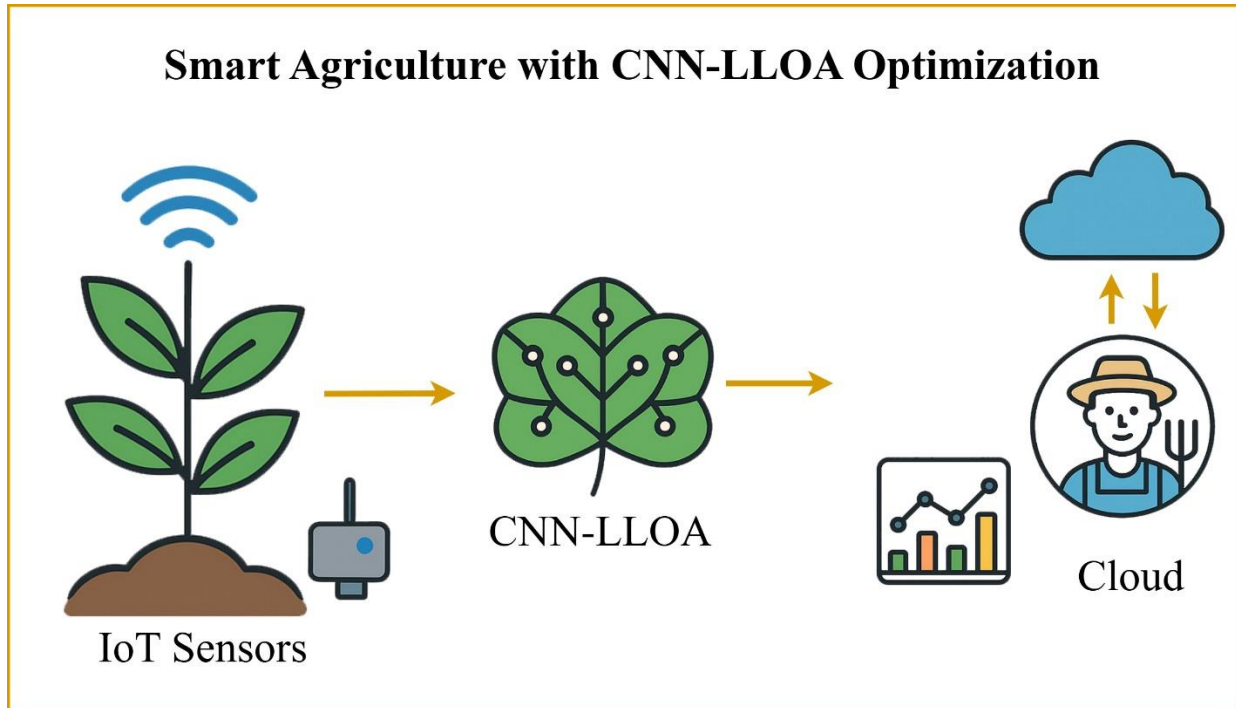
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24 **Graphical Abstract:**



25

26 **ABSTRACT**

27 Indian agriculture, the backbone of the country's economy, faces significant challenges due to
28 climate change and crop diseases. Soil productivity is highly dependent on water availability and
29 seasonal variations in India. In addition, environmental changes in neighboring regions also
30 contribute to global warming. Climate variability intensifies the outbreaks of diseases, threatening
31 food security. This research aims to enhance precision farming in India by proposing a smart
32 agricultural framework using IoT (Internet of Things) sensors, advanced routing algorithms,
33 machine learning (ML), and reinforcement learning (RL). With the help of environmental and
34 crop-related data like soil moisture, temperature and humidity the framework can resourcefully
35 utilize resources, improve yield, protect the climate, and ensure resiliency to climate change.
36 Information such as temperature and crop health is measured by strategically positioned IoT
37 sensors across farmlands and sent through the Bee Guided Routing Protocol (BGRP) and Energy

38 Efficient Routing Protocol (EERP) for proper management of data flow. Farmers and agricultural
39 specialists can make informed decisions due to the processing, storing, and computing capabilities
40 offered by Cloud technologies, which facilitate easy access to data. The proposed hybrid
41 Convolutional Neural Network–Lotus Leaf Optimization Algorithm (CNN-LLOA) refines and
42 processes the dataset to improve prediction accuracy. Anomalies like insect and disease
43 infestations, anomalies, and agricultural yield are predicted alongside the detection of crop
44 conditions.

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

47

48 **1. Introduction**

49 Agriculture plays a vital role in the economic development of many countries, particularly in
50 developing regions. However, climate change, water scarcity, soil degradation, and pest
51 infestations continue to pose major challenges to agricultural productivity. Other developing
52 nations facing similar climatic and agricultural challenges can also adopt the proposed model. The
53 framework can adapt to various environmental and geographical conditions because it integrates
54 cloud computing, machine learning algorithms, and Internet of Things (IoT)-based sensing. With
55 minor modifications, the model can be applied in countries across Asia, Africa, and Latin America
56 that experience issues such as water scarcity, irregular rainfall, soil degradation, and pest
57 infestations. The CNN-LLOA's adaptability and the IoT sensor network's modular design enable
58 modification according to regional crop varieties, climate zones, and soil properties. Additionally,
59 the framework is economically feasible for low-resource areas due to the utilization of inexpensive
60 sensors and energy-efficient routing protocols like BGRP and EERP. Agriculture is the cornerstone

61 of many nations, including India. Water shortages often occur depending on location and seasonal
62 conditions (Dilip Charaan & Therasa, 2022). Farmers traditionally evaluate soil conditions and
63 make crop decisions based on experience and assumptions. However, climate conditions,
64 humidity, and water levels were often not considered adequately, which negatively affected
65 farmers (Naresh & Munaswamy, 2019). India's agricultural land area is projected to reach over
66 130 million hectares by 2024. This is for the production of food grains. If current population
67 growth rates continue, the World Bank projects that more than half of all food will need to be
68 produced before 2050. However, current climate change will not support such huge agricultural
69 production. Consequently, advanced farming is becoming more and more necessary (Reddy et al.,
70 2020).

71 Every society's social structure, economy, and environment are significantly impacted by this
72 crucial industry. Agriculture's development in food and cattle production has enabled significantly
73 more human population increase than hunting and gathering could (Deepa et al., 2021). Rain-fed
74 agriculture, irrigation systems, and groundwater irrigation are all at risk due to the growing demand
75 for water, which reduces agricultural productivity in areas where irrigation is required (Patil et al.,
76 2023).

77 Many agricultural difficulties are exacerbated by global climate change (Paudel et al., 2023). Due
78 to water constraint brought on by droughts, heat waves, and floods, crop productivity frequently
79 declines when temperatures rise and weather patterns shift (Kim & Lee, 2023). Thus, crop failures
80 that happen concurrently in several locations may become more likely as a result of climate change.

81 A conceptual framework called climate-smart agriculture (CSA) provides possible answers to
82 these complex issues (Borrelli, 2023). Implementing measures that enhance adaptation, reduces
83 greenhouse gas emissions, and maintains national food security can lead to sustainability in

84 agriculture (Raihan, Ridwan, & Rahman, 2024). Farmers learn about pH level, temperature, and
85 soil with smart farming techniques.

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

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

103 According to Sekaran et al., (2020), the verification of the thought has been around for some time,
104 however, it is increasingly being undertaken as a result of recent developments of hardware
105 technology. Through IoT, physical gadgets can communicate with the internet to detect, collect,
106 store and prepare data (Senthil Kumar et al., 2021). IoT provides data for monitoring agricultural

107 environments through wireless sensor networks (WSNs). It decides on the data of the plants. The
108 smart farming system's monitoring capabilities can be enhanced and the network's scalability
109 increased by adding more sensor nodes to the current WSN (Koshariya et al., 2023). The prediction
110 engine sends information to the notification server, which then forecasts the outcomes (Gupta &
111 Nahar, 2022).

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

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

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

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

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

151 IoT, cloud computing, AI, and machine learning have all significantly advanced precision
152 agriculture; yet, a number of drawbacks and problems still exist in the models that are currently in

153 use. Despite their heavy reliance on sensor networks and data collecting, many existing systems
154 frequently suffer from restricted scalability across broad or diversified farmlands, energy limits,
155 and intermittent or unreliable connectivity. Furthermore, while though AI models like ensemble
156 classifiers, AGRU, and neural networks increase prediction accuracy, they can be computationally
157 demanding, needing sophisticated infrastructure and a lot of computing power, which not all
158 farmers may be able to afford. Existing frameworks are less robust in real-world situations because
159 they frequently lack the flexibility to adjust to different climatic zones, crop types, and
160 unanticipated environmental abnormalities.

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

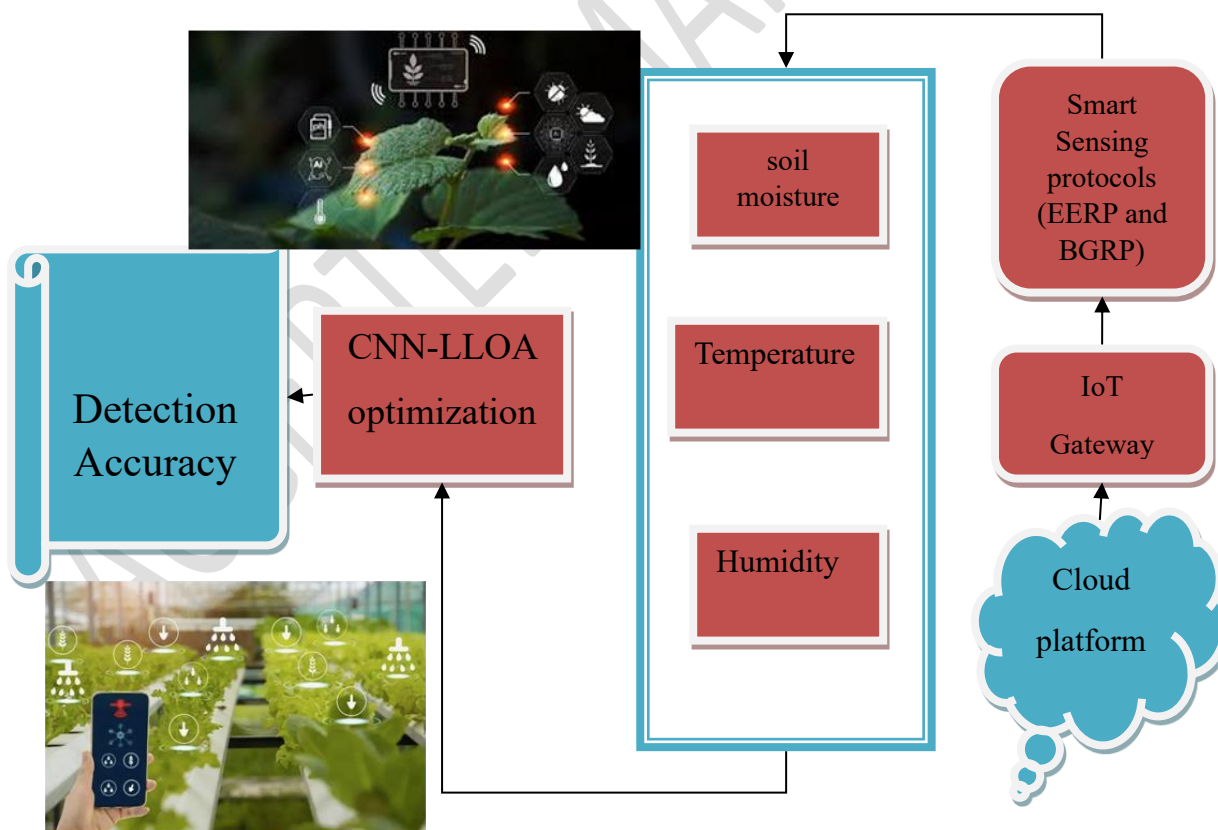
- 162 • The research introduces a smart farming architecture integrating IoT sensors, cloud
163 computing, and ML/RL algorithms to improve precision farming in India.
- 164 • Utilization of BGRP and EERP ensures effective and energy-efficient data transmission
165 from IoT sensors across farmlands. Strategic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

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

176 **2. Materials and Methods**

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

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



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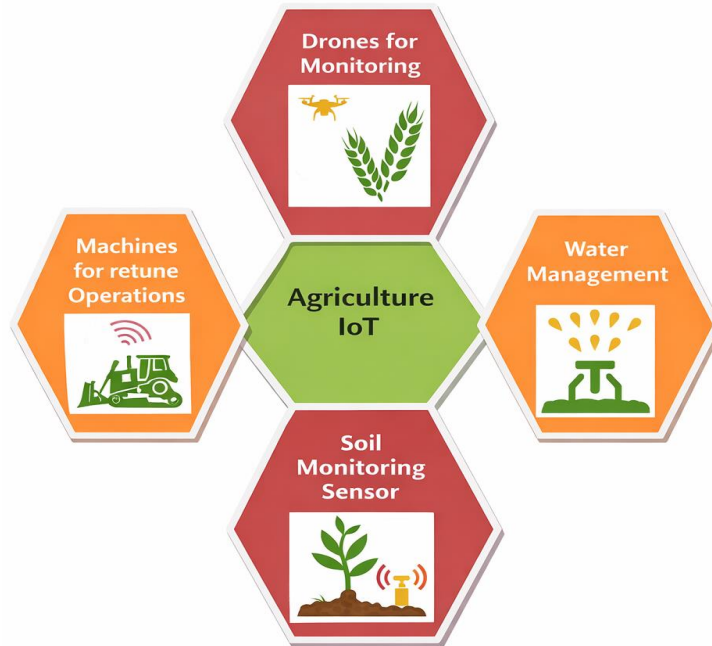
Figure 1. Proposed block diagram for an IoT-based smart agriculture system.

189 *2.1 Cloud Computing*

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

196 *2.2 Smart Agriculture with IoT*

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



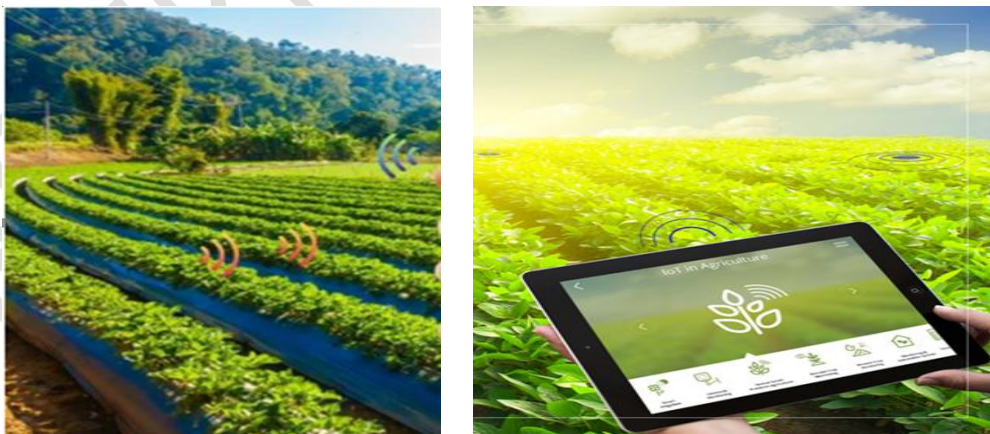
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Figure 2. Overview of an agriculture IoT.

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

211 *2.3 IOT-based Smart Agriculture Monitoring in WSN*

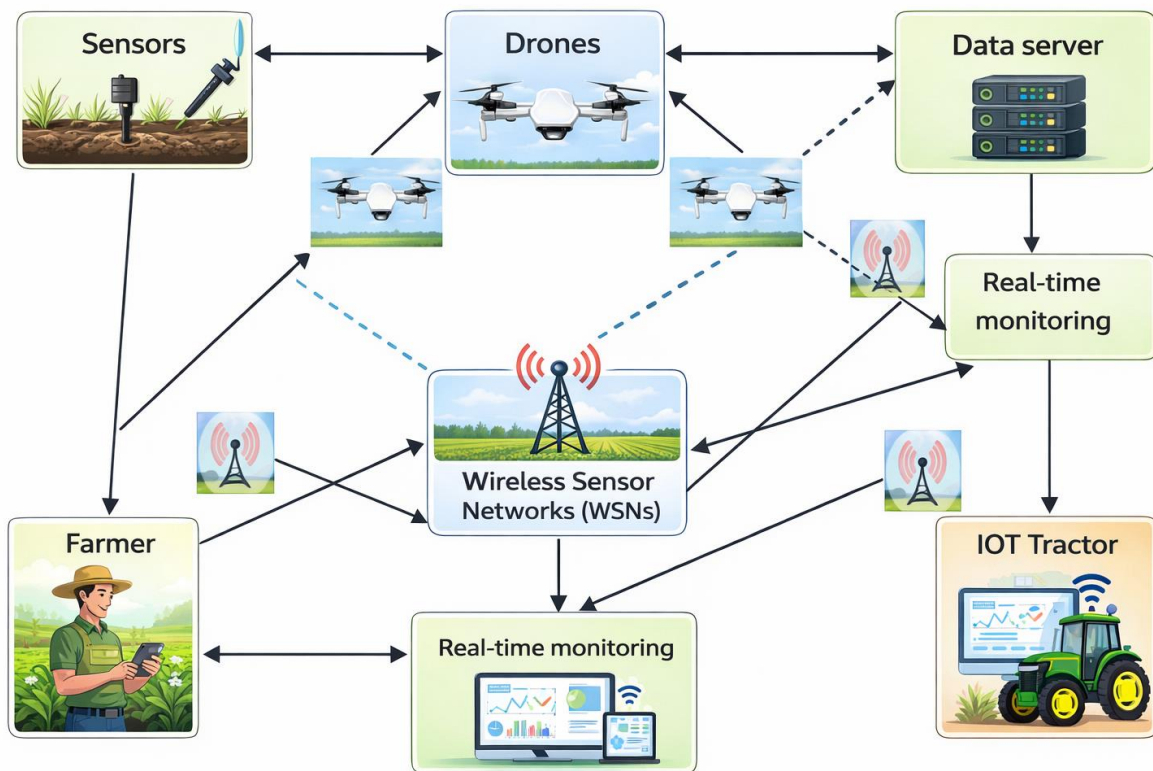


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Figure 3. IOT-driven smart agriculture oversight.

213 Datang Mobile introduces the Wisdom Agriculture system, an IoT solution for agriculture. Figure
 214 3 depicts an operational IoT-based smart agriculture sensor monitoring system. It depicts a lush
 215 green agricultural landscape complete with sensor nodes that communicate data via WSN, as
 216 depicted by the signal icons radiating from the crops. A smartphone in the foreground shows a
 217 smart farming application interface with real-time environmental metrics like sunshine intensity,
 218 temperature, humidity, soil moisture, and plant health status. This configuration illustrates how
 219 farmers can employ IoT technology for remote monitoring and management of agricultural
 220 conditions, allowing them to make well-informed choices regarding crop health, fertilization, and
 221 irrigation. The background of the image, featuring mountains and nature, highlights the
 222 technology's value in rural and semi-remote agricultural regions.

223 *2.4 IoT Device and Sensors*



224

225

Figure 4. IOT-based smart agriculture monitoring system.

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

233 *2.5 EERP and BGRP Protocol in WSN*

234 EERP and other energy-efficient routing protocols are vital for the long-term operation of field-
235 deployed devices, especially in remote, low-energy agricultural areas. The BGRP routing protocol
236 draws its inspiration from the foraging of bees, which is known to be effective. It is useful to WSNs
237 due to its efficient and adaptive routing schemes.

238 Bee-Guided Routing Protocol (BGRP) and Event-Driven Energy-Efficient Routing Protocol
239 (EERP) combined to offer a hybrid solution with improved functionality of Wireless Sensor
240 Networks (WSN) in smart agriculture. By including the advantages of both strategies, the hybrid
241 protocol provides the data transport reliability and energy efficiency.

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

248 guarantees fast, low-latency communication to the cloud while ensuring the robustness and energy
249 efficiency of the IoT network.

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

255 *The hybrid model incorporates several key features:*

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

268 The overall hybrid approach may apply in smart agriculture scenarios for better results and
269 increased efficiency. For agriculture, it ensures coherent supply and significantly increases energy
270 efficiency. Through the algorithm, the growers can give preference to unattended critical

271 conditions and respond on time. The algorithm will assist in agricultural monitoring. By using
272 effective load balancing the costs of network maintenance will be reduced and its operating life
273 will be increased. The protocol is reliable and adaptable to changes in dynamic agriculture
274 scenarios that ensures performance and success.

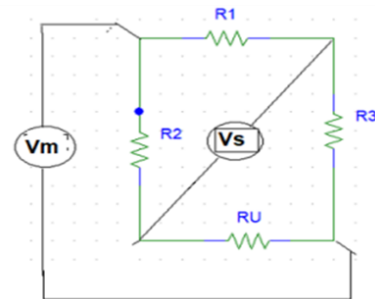
275 In the agricultural sector, IoT technology depends significantly on a variety of sensors. The system
276 consists of three layers: the sensor layer, transport layer, and application layer. They serve the
277 following functions:

278 2.5.1 Soil Moisture

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



(a)



(b)

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

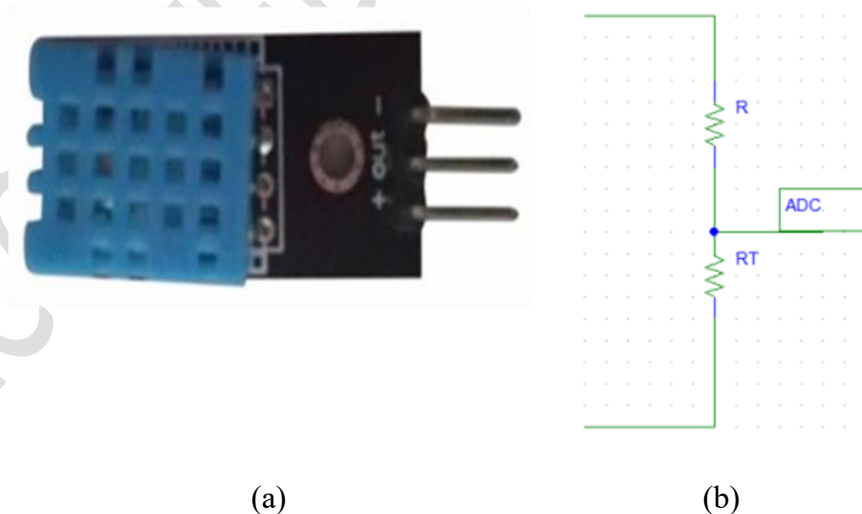
285
286 Resistance is a measure of soil moisture content. The following formula is used to measure the
287 unknown soil resistance that is a component of the Wheatstone Bridge:

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

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.

2.5.2 Sensor for Humidity 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.



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

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

$$306 \quad RH = \left(\frac{\rho_\omega}{\rho_s} \right) \times 100\% \quad (2)$$

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

310 2.5.3 pH Sensor

311 Soil pH measurement is carried out using the liquid pH0-14, shown in Figure 7. It ascertains which
312 types of substances are found in the soil. To measure the activity of hydrogen ions in soil, the pH
313 sensor (Prakosa et al., 2022) is utilized. For plants to thrive, the average pH level of the soil should
314 range from 6.5 to 7.5. Different species of plants need varying pH levels in order to flourish. The
315 soil's pH level can be affected by the type of soil used for plant growth, the quantity of fertiliser
316 applied, and the amount of water used. In order to conduct this experiment, the cactus plant
317 requires a pH level of 5 to 7. Before measuring the pH of the soil, a buffer solution is used to
318 calibrate the pH sensor.



319

320

Figure 7. pH Sensor

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

$$322 \quad E(T) = E^{\circ}T - 0.1984T \text{ pH} \quad (3)$$

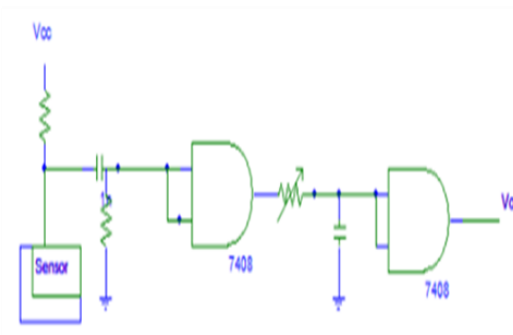
323 Where $E(T)$ represents the measured electrode potential, $E^{\circ}T$ denotes the standard electrode
324 potential, T represents the absolute temperature in Kelvin, and pH denotes the hydrogen ion
325 concentration level of the solution.

326 2.5.4 Vibration Sensor

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



(a)



(b)

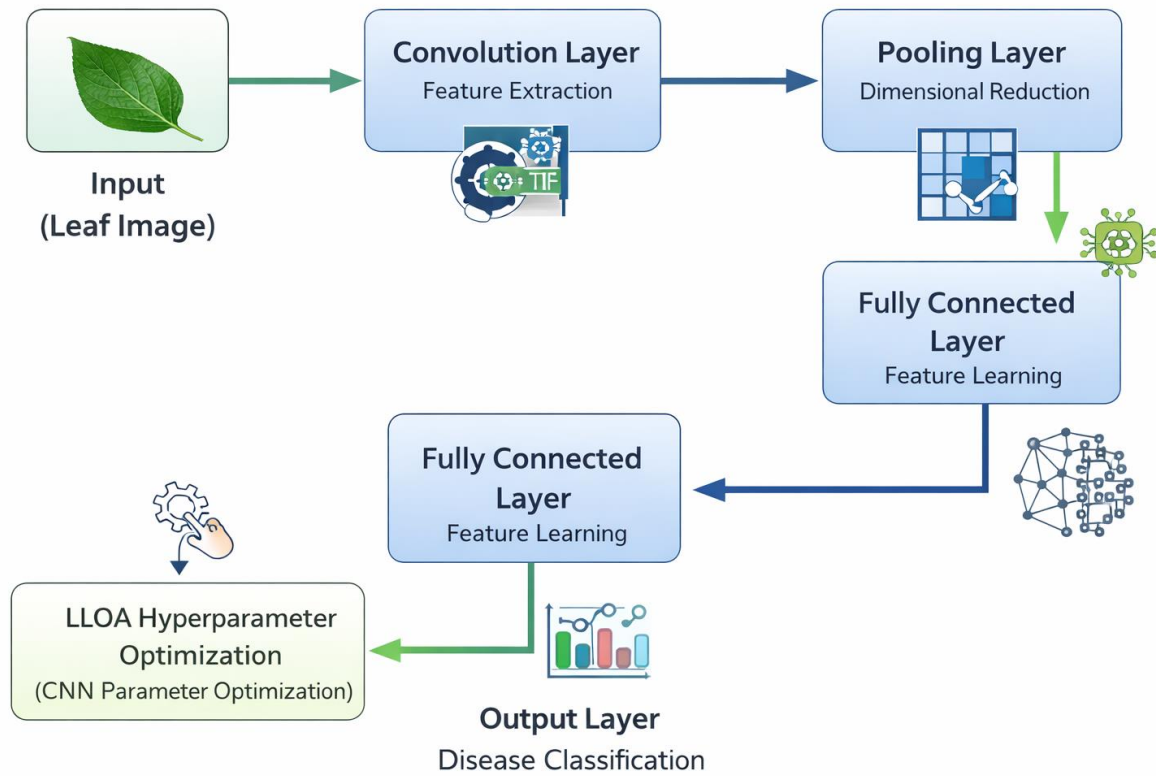
338 **Figure 8.** (a) Vibration Sensor, b) Vibration Sensor Equivalent Circuit

339 *2.6 Hybrid Approach CNN- LLOA Classifier*

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

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

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



361

362

Figure 9. Hybrid CNN- LLOA classifier overview diagram

363

2.6.1 Convolutional Neural Network (CNN) as the primary

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The convolutional layers apply filters to pull various information from the input images. More

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complex features relevant to the diseased classes are captured in the deeper layers as the early

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layers capture simple features like edges and textures. Usually, a convolutional layer would be

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followed by a ReLU activation function and may be prevented by Batch Normalisation. Max-

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pooling layers reduce memory usage and computation in a neural network with no significant loss

369

of accuracy. It works by down-sampling the input representation, reducing its dimensionality and

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retaining only the most essential features. The final flattened representations are processed by fully

371

connected (dense) layers following some convolutional and pooling layers. The output classes

372

(healthy vs. various ill categories) are mapped to the learned features via these layers. The output

373 layer uses a SoftMax activation function to produce class probabilities and is made up of neurons
374 that correspond to the classes (healthy, disease type 1, disease type 2, etc).

375 2.6.2 LLOA optimizer

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

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

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

388 2.6.3 Training and Validation Process

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

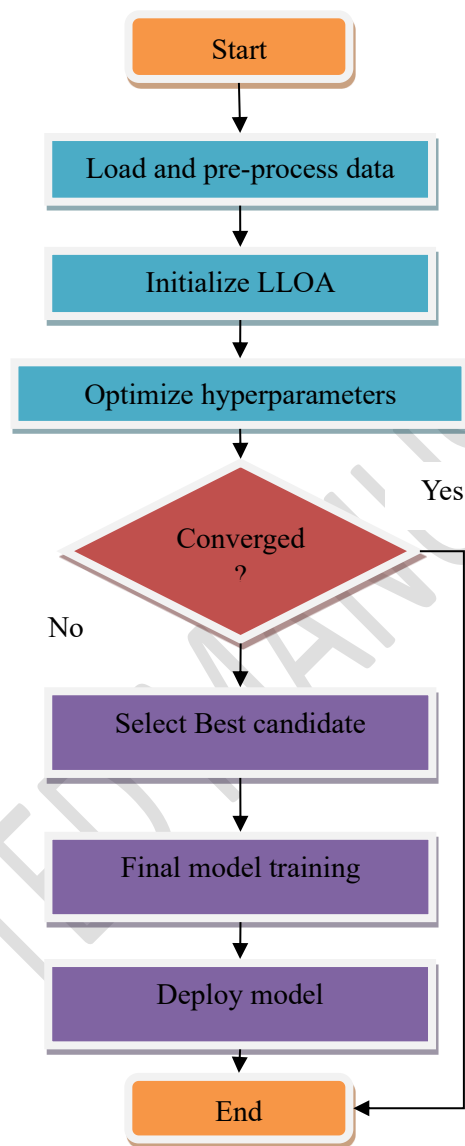
393 For the purpose of this research and analysis, the CNN-LLOA was selected as it combines the
394 optimization capabilities of the self-adaptive LLOA with the feature extraction capabilities of
395 Convolutional Neural Networks (CNNs) to handle complex agricultural datasets. In the field of

396 deep learning, CNN refers to Convolutional Neural Network which is likely to be extensively used
397 to identify spatial and visual patterns in images. Yet, other issues such as overfitting, difficulty in
398 tuning parameters and local minima traps plague CNNs alone. Taking a cue from lotus leaves'
399 adaptive water-repelling and natural-self-cleaning characteristics, the LLOA component addresses
400 these drawbacks and enables the CNN model to facilitate an effective global search, quicker
401 convergence and ideal weight tuning. Compared with other hybrid optimization strategies, CNN-
402 LLOA generates more accurate solutions in changing situations at a lower computational cost with
403 greater stability. The bio-inspired flexibility of smart farming applications boosts their prediction
404 accuracy, energy efficiency and real-time performance thanks to an improved robustness to noisy
405 and non-linear agricultural information.

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

410 The Hybrid CNN-LLOA classifier's flowchart, which depicts the step-by-step process of model
411 construction and optimization, is depicted in the Figure 10. Preprocessing, which involves
412 cleaning, resizing, and normalizing raw agricultural data, comes first. After that, a population of
413 random hyperparameter candidates is created by initializing the Lotus Leaf Optimization
414 Algorithm (LLOA). Hyperparameter optimization is the next step in the process, when each
415 candidate is assessed according to model performance. In the event that the optimization has not
416 converged, fresh candidates are created and reevaluated by a decision node. The best candidate is
417 chosen for final model training using the optimum CNN configuration after convergence is

418 reached. The cycle from data collection to implementation is then completed when the trained
419 model is put into practice for precision agriculture.



420

421

Figure 10. Flowchart for Hybrid CNN-LLOA classifier

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

```

422 2.7 Performance Measures

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

$$425 \text{ Accuracy} = \frac{TP}{TP+TN+FP+FN} \quad (4)$$

$$426 \text{ Sensitivity} = \frac{TP}{TP+FN} \quad (5)$$

$$427 \text{ Precision} = \frac{TP}{TP+FP} \quad (6)$$

$$428 \text{ Recall} = \frac{TP}{TP+FN} \quad (7)$$

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

438 **3. Results and Discussion**

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

446 Real-time field data collected from different agricultural regions in India were used in MATLAB
447 to visualize the eight field characteristics. The dataset was used for training and validation in this
448 study. In order to continuously monitor environmental and crop-related factors like soil moisture,
449 temperature, humidity, pH level, nutrient content, and leaf wetness, IoT-enabled sensors were
450 strategically placed throughout farmlands. To increase the variety and resilience of the training
451 samples, this real-time data was combined with satellite imagery and historical meteorological

452 data. To guarantee that the suggested hybrid CNN-LLOA could learn efficiently from real field
 453 conditions, enabling precise detection, prediction, and decision-making in precision agriculture,
 454 the gathered datasets were subsequently pre-processed and separated into training and validation
 455 subsets. The final structure that best reflects the model performance according to the evaluated
 456 criteria is shown in Table 1.

457 **Table 1.** CNN-LLOA hyperparameter configuration.

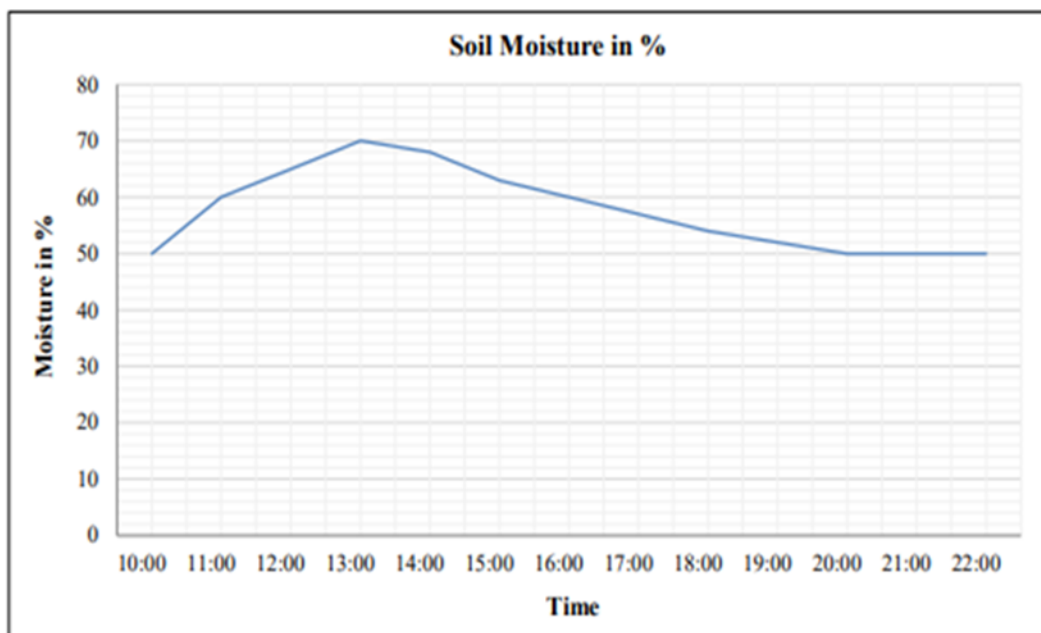
Parameter	Value
Normalization layers	1–2
Epochs	22
Kernel size	3×3
Number of nodes per layer	100
Optimizer	RMSProp
Dropout rate	0.3 – 0.5
Learning rate drop factor	0.1
Activation function	ReLU
Convolution layers	1–3
Pooling type	Max pooling / Average pooling
Batch size	9

458

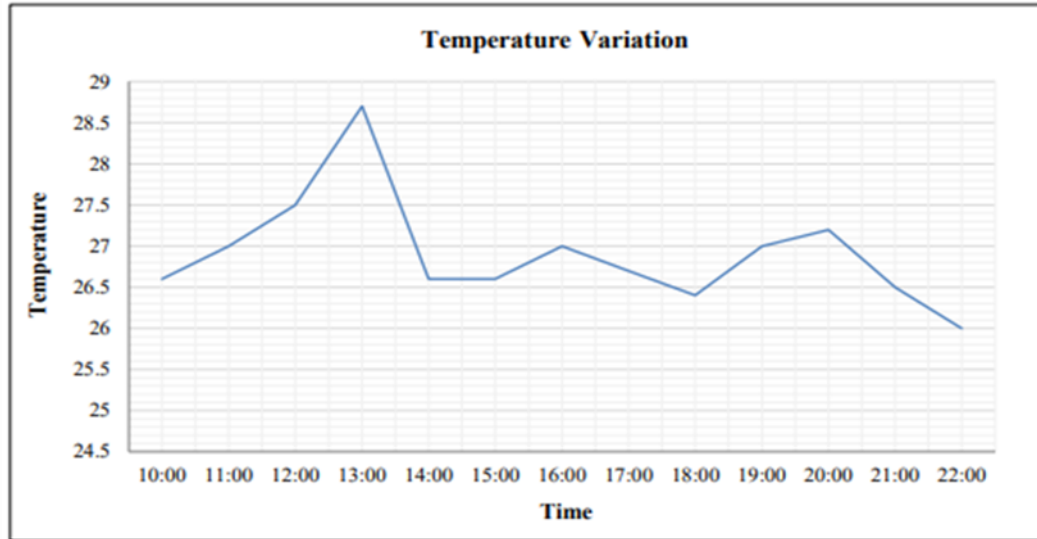
459 *3.1 Sensor result using EERP and BGRP Protocols*

460 The irrigation data for several sensors, including moisture, temperature, and humidity. When it hits
 461 the threshold level, the device sends an appropriate action to the fieldwork robot. Figure 8 depicts
 462 the irrigation of raw data information using moisture, temperature, and humidity sensor outputs.

463 This continuous graph depicts well-performed device activities during the feedback processing
464 period.



465
466 **Figure 11.** Result from soil moisture sensor data using EERP and BGRP Protocol.
467 Water is provided every hour from 10 a.m. to 1 p.m. As the plant is given more water, the total
468 amount of water in the soil rises; this can be tracked. At 10 a.m., the value under examination is
469 50%, and at 1 p.m., it is 70%. A graph illustrating the time-related changes in moisture content is
470 shown in Figure 11. One can induce trembling in the plant by placing a high-speed fan at a short
471 distance from it and turning it on. monitoring the vibrations of the system and adjusting the speed
472 of the fan.



473

474

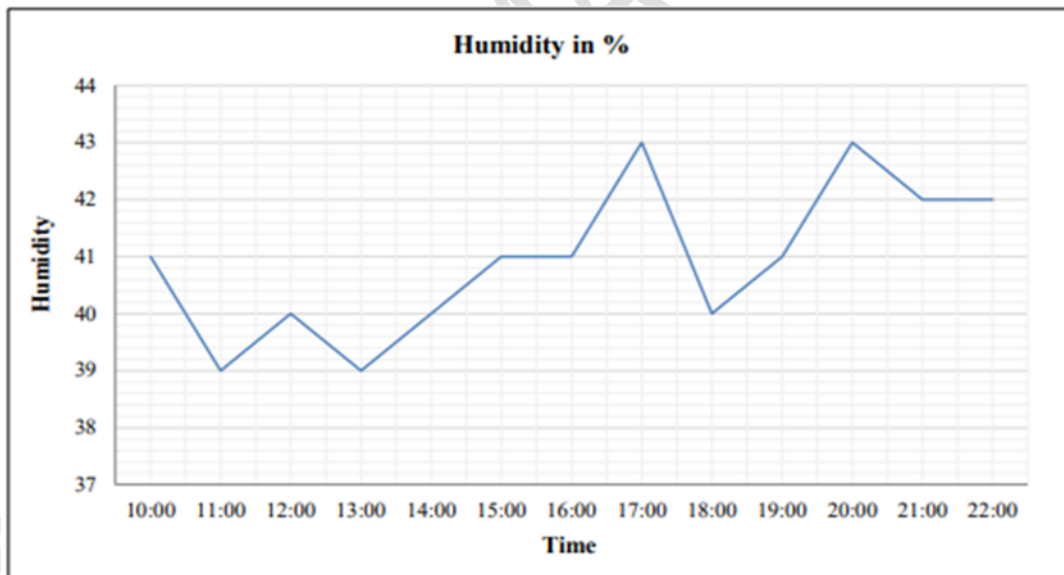
Figure 12. Result from temperature sensor data using EERP and BGRP Protocol.

475

The range of temperatures is 26 to 28.7 degrees Celsius. Around one in the afternoon, the day's

476

highest temperature is reached. Figure 12 illustrates this variation through charting.



477

478

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

479

In the vicinity of the plant, humidity levels hit their nadir at about 7 p.m. and their zenith at 10

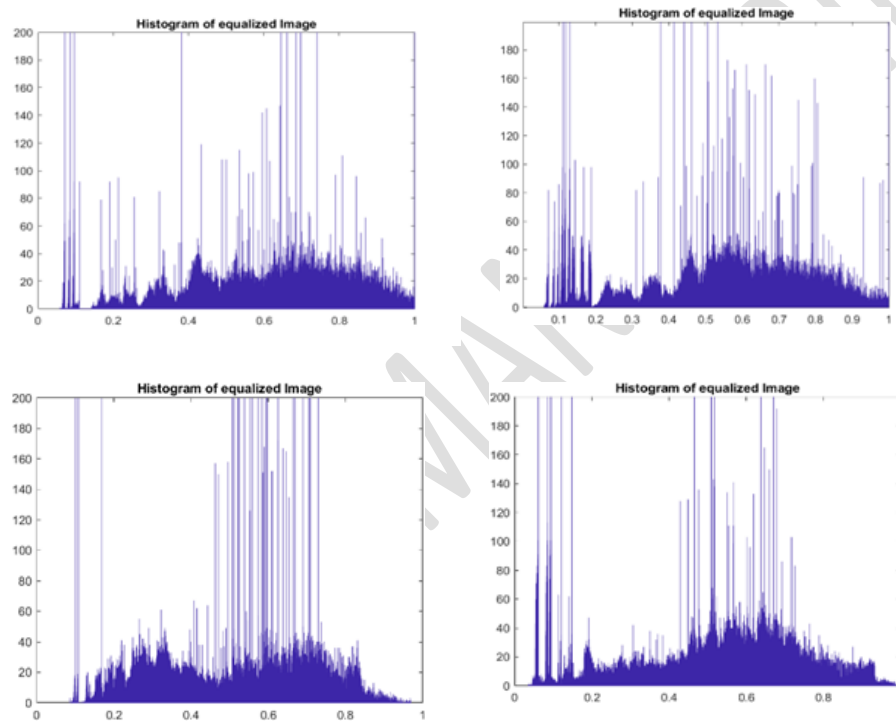
480

a.m. Figure 13 illustrates the development of humidity levels.

481

482 *3.2 Histogram Representation*

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



488 **Figure 14.** Histogram of equalizes images.

489 *3.3Confusion Matrix*

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

		Predicted class		
		Non-affected	Affected	
True class	Non-affected	143%	1%	99.3%
	Affected	2%	183%	98.9%
		98.6%	99%	99.1%

494

495

Figure 15. Confusion Matrix.

496 Table 2 and 3 shows the results of fine-tuning methods like Xception, RegNetx002,

497 MobilenetV3small, a comparison of training accuracy in proposed CNN-LLOA.

498 **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

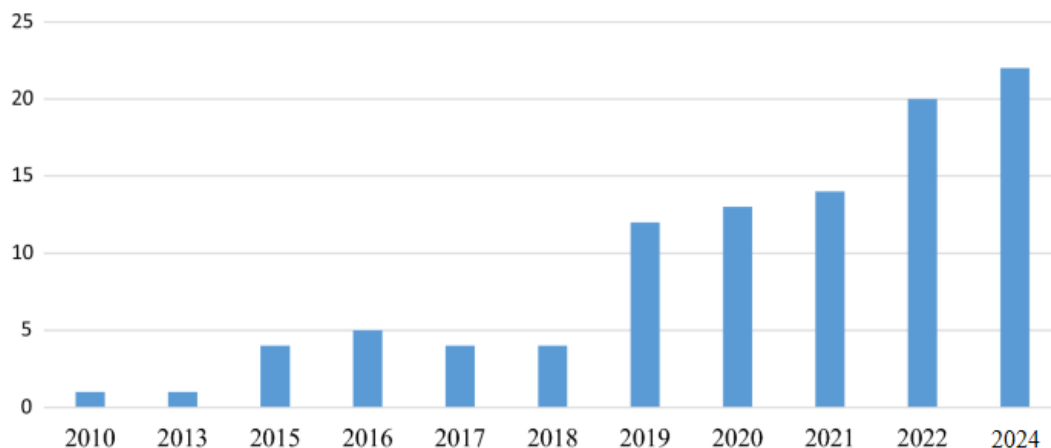
499

500 **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

501

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



504

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

506 4. Conclusion

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

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