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Article

Optimized smart farming using WSN–IoT and multi-strategy improved zebra optimization algorithm-MIZOA

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Abstract: The survival of the human community depends on the agricultural industry. Various measures have been implemented to boost agricultural productivity. But frequent pest infestations and harsh environmental conditions are the main causes of agricultural loss. In a scenario like this, combining cutting-edge IoT technologies, such as advanced sensors, could boost agricultural productivity and minimize financial loss. Indian agriculture's problems with low production, wasteful resource use, and climate variability have given rise to smart farming as a potential remedy. An optimized smart farming framework for India is presented in this research, utilizing a Several Strategies enhanced Zebra Optimization Algorithm (MIZOA) in combination with an Internet of Things (IoT)architecture of the Wireless Sensor Network (WSN). An IoT-based smart agriculture monitoring system that uses wireless sensor networks (WSNs) and predictive analytics to track important environmental elements The system makes proactive decisions for the best fertilization, irrigation, and pest control by using machine learning techniques for predictive analytics and WSNs to collect data from dispersed sensor nodes machine learning techniques for predictive analytics and WSNs *-2`to collect data from dispersed sensor nodes. The Improved Zebra Optimization Algorithm with Multiple Strategies (MIZOA), an enhanced version of the ZOA, is proposed in this study to overcome these issues. Furthermore, the predictive analytics component forecasts environmental conditions with a 94 % accuracy rate, which helps with timely interventions and reduces crop stress. Scalability for a range of agricultural applications, such as precision farming and greenhouse monitoring, is provided by this Internet of Things-based technology, which also promotes sustainable farming methods.

Keywords: smart agriculture, wireless sensor networks (WSN), internet of things (IOT), multi-strategy improved zebra optimization algorithm-MIZOA, sensor

1. Introduction

In addition, smart farming has embraced IoT technology, which farmers use to track crop yields, assess soil moisture levels, and use drones to help with tasks like pesticide application. The challenges of protecting Cybersecurity risks and weaknesses in smart agricultural settings increase as more equipment connect to the Internet. The vast array of digital technology and data applications that are currently available in agriculture supports the notion that digitalization represents the fourth agricultural revolution. Smart farming was born because of the ability of IoT sensors to collect data about their agricultural field in real time. To meet the nation's needs for food supplies, the agricultural sector is crucial [1]. For the Smart Farming (SF) applications, the researcher focused on IoT-enabled WSNs. These days, SF is necessary to increase farm productivity while reducing expenses and resources. Agricultural sensors are positioned across the farm to collect information that is subsequently transmitted electronically to the base station to monitor and make decisions about agriculture [2].

Precision agriculture and farming (PAF) use the IoT o process the effective communication of multiple wireless sensors in order to boost farmer output. Throughput maximization, latency reduction, high signal-to-noise ratio (SNR), minimum mean square error, and enlarged coverage area have all been considered when studying WSN architecture [3]. Gathering data on the field's soil parameters is part of the monitoring procedure. In order to gather these data and periodically upload them to the cloud, establishes a wireless sensor network (WSN) [4]. The system optimizes the irrigation cycles by using online meteorological data and relays to operate actuators to irrigate the crops, such pumps [5].

The use of localization in agriculture, encompassing environmental conditions, precision agriculture, crop monitoring, and animal management is also covered in the study [6]. As demonstrated in India, farmers who employ IOT devices for drip irrigation can greatly boost water efficiency by using their cell phones to remotely control watering. In Africa, agricultural yields have increased and fertilizer use has decreased because precision farming uses sensor networks. Food security, environmental impact, and sustainable farming methods can all be greatly improved by implementing IOT and sensor networks at the application layer, especially in developing nations [7].

Farms can operate without human labor thanks to the IOT. It has a number of possible uses in agriculture, such as greenhouse farming, large-scale farming, and management. Sensors are the most crucial component of the IOT. The main purpose of sensing devices is to gather information about the soil and its environment [8]. A list of available sensors is given for use in agriculture particular uses such irrigation, harvest placement, soil foundation, and insect and identification of pests. In this paper, we suggested an Internet of Things-based WSN framework with several design levels for smart agriculture [9,10].

The Contribution of the following paper:

- A smart farming framework designed especially for Indian agricultural circumstances that combines Wireless Sensor Networks (WSN) enable real-time monitoring.
- Smart agriculture powered by IoT has been extensively studied, with a growing focus on enhancing smart agricultural practices with WSNs and data analytics.
- By optimizing crucial agricultural parameters including fertilizer distribution, irrigation timing, and energy use, the suggested MIZOA reduces water consumption, lowers operating costs, and increases crop production.
- By streamlining the routing and cluster head selection process in WSN, the algorithm dramatically lowers energy consumption and extends network life time two critical factors for India's remote and rural farming contexts. Hierarchical clustering-based dynamic data fusion.

The paper is organized as follows: The section 1 introduces the concepts and highlights the necessity of the endeavor. Section 2 contains the pertinent works. The suggested technique for the paper is presented in Section 3. Section 4 contains the findings and commentary. Finally, section 5 has the conclusion.

2. Related works

Karothia et al. [11] the suggested gadget is intended to serve as a tool for collecting and analyzing agricultural data and research as well as for measuring agricultural parameters. The gathered data will be available for research purposes worldwide. A 32-bit microprocessor, Numerous sensors, Wi-Fi, a power management device that runs on rechargeable batteries, cloud and local storage, an online user interface (UI) make up the portable gadget.

Singh et al. [12] this work presents a platform to organize Multirotor UAVs are used to collect data on agricultural crops. The information service system is made to gather positioning and crop data from UAVs in real-time using the Django framework. Using the suggested architecture, a thorough performance analysis is carried out for crop sensing and monitoring. With a coverage efficiency of 96.3 %, the suggested design shows great promise for agricultural applications like monitoring crop health and applying pesticides and fertilizers.

Kumar et al. [13] numerous studies in ML and Agriculture 4.0 are used to choose the weather and soil factors. The several patents and the weather station's design created are also contrasted in the essay. The technology created in this article offers a cutting-edge and reasonably priced way to monitor local weather.

Chandrasekaran et al. [14] the proposed system performs better in terms of throughput than other methods like OSEAP, E2S-DRL (60 Mbps), and EQSR (12.5 Mbps) with an impressive throughput number of 68 Mbps. At 90.9 %, the packet delivery ratio (PDR) for the suggested method is likewise much higher. The suggested method can greatly enhance the functioning of IoT-enabled smart agriculture solutions that increase farmer income and crop productivity.

Rao et al. [15] an effective, safe, blockchain-based cluster-based routing system is presented in this research to tackle these problems. After node IDs are assigned, the system selects Cluster Heads (CHs) based on energy, neighbor count, and distance from the Base Station (BS) using Distributed Fuzzy Cognitive Maps (DFCM). DFCM strives for a balanced CH distribution in order to optimize energy consumption. The proposed technique offers a significantly higher rate of convergence, with a detection rate between 75 % and 90 %. Our Blockchain-Based Integrity Checking and Optimal Secure Cluster-Based Routing Protocol provides a comprehensive and superior way to enhance the security, robustness, and effectiveness of WSNs in smart agriculture.

Kilaru et al. [16] the study shows how to use weather forecasts and wireless sensor networks (WSN) to automate agriculture. WSN is more effective than IoT since it does not link every sensor node to the Internet directly, which lowers Internet traffic and sensor network energy consumption. A clustering tree topology is used by the system to grow its operational range, improve connection, and quickly add new nodes on the fly. Local gateways are the branches, global gateways are the root node, and sensor nodes are the leaves.

Akilan et al. [17] ResNet50 is then used to extract and classify features from pre-processed pictures. In the event of severe weather or poor soil conditions, the devices will immediately take corrective action based on these forecasted facts. On the other hand, farmers will receive an alarm message about the terrible circumstances and the presence of illnesses and pests. The suggested approach performs better when tested using a number of measures, such as 98 % accuracy for field monitoring and 94 % accuracy for weather forecasting. As a result, the suggested IoT and deep learning-based approach can help farmers produce large amounts of crops in a shorter amount of time.

Neena et al. [18] this study carried out a comprehensive examination of a large number of proposed technologies for the agricultural sector. We have pulled up a list of clever agricultural uses and suggested a taxonomy to categorize them. Connectivity and network infrastructure continue to be the main issues facing rural communities. This study investigates if integrating machine learning with IoT-based technology is feasible techniques to optimize resource use, planning and production, marketing, pesticides choice, pricing prediction, and other agricultural issues.

Singh et al. [19] in actuality, wireless sensor networks overcome all these issues, and contemporary precision agriculture is quickly embracing the technologies underlying wireless sensor networks. In this work, we offer a technique for wireless sensor network-based pest monitoring by merely identifying insect behavior through a variety of sensors. Based on five significant crops and related insect pests, we suggested a quick and precise method for identifying and classifying insects. This technique gathers information from sensors positioned across the field to analyze insect behavior. According to the findings, the suggested work increases the accuracy of the current work by 3.9 %.

Bhatia et al. [20] this study evaluates current wireless protocols and examines their impact on the implementation of IoT-WSN-enabled smart farming. It enumerates the essential elements of the IoT-WSN concept for intelligent farming. It demonstrates some characteristics of various technologies that are suggested by IoT-based farming methods. This paper offers a comprehensive overview of the function of relevant technologies and existing protocols in smart farming, along with a detailed examination of the wireless standards used in IoT-WSN based smart farming. The representation of the basic energy consumption states for Zigbee, Sigfox, LoRa WAN, and NB-IoT end-devices is explained in the document. The effects of energy-efficient LoRa WAN technology and the suggested WSN-IoT implementation strategy are highlighted in this paper.

Burugari et al. [21] smart technologies are being used in the agriculture industry to improve it. GPS, cloud-based services, IoT, and big data are among the technologies that are becoming more and more significant in the agricultural sector. The need is growing because of need for more accurate agricultural analysis, the conversion of real-time field data, and automated farming methods for future advancement. With the application of these clever strategies, a smart agriculture sector is anticipated to emerge. The authors have covered the advantages and disadvantages of IoT as well as several kinds of sensors for data collection in this chapter.

Praveen et al. [22] this article examines the primary subjects of food supply networks, agricultural commerce, farm insurance, and smart farming. It is the dependable method of data storage that facilitates the advancement of many parts of the information-driven instruments that make agriculture smarter. Blockchain technology is developing into a complete, all-encompassing technology that can be applied to almost any intelligent application created for the Internet's next generation. Every node in the blockchain, which is a growing technology, is a component of a distributed register that enhances data security and transparency.

3. Proposed system

To monitor various factors, sensors can be positioned throughout a field or buried in the ground common sensors. These sensors gather information about the conditions in the field in real time. To collect data and capture close-up pictures, drones with cameras and other sensors can fly over fields. This can be especially helpful for monitoring the general development of the crop, determining regions of illness or stress, and evaluating the health of the crop. Using web services IoT platforms is a popular way to transfer sensor and drone data to a central system. This data may contain information regarding weather patterns, soil conditions, crop health, and other subjects. IoT enables precision farming by collecting and analyzing data from sensors placed around the farm. Temperature, humidity, soil moisture, nutrient levels, and even crop health can all be monitored by these sensors. By using this information to improve irrigation, fertilization, and pest control, farmers may increase productivity and resource efficiency.

IoT enables farmers to use wearables and linked sensors to Observe the livestock's behavior and overall health. By regularly monitoring variables like location, exercise level, and body temperature, farmers may spot disease indications, modify feeding schedules, and improve overall animal welfare. The IoT has several uses and advantages for smart agriculture by combining different sensors and technology, transforming the industry. The suggested block diagram work flow for IoT and web services-based smart agriculture is shown in **Figure 1**. Drones, harvesters, and tractors can all be automated thanks to IoT.

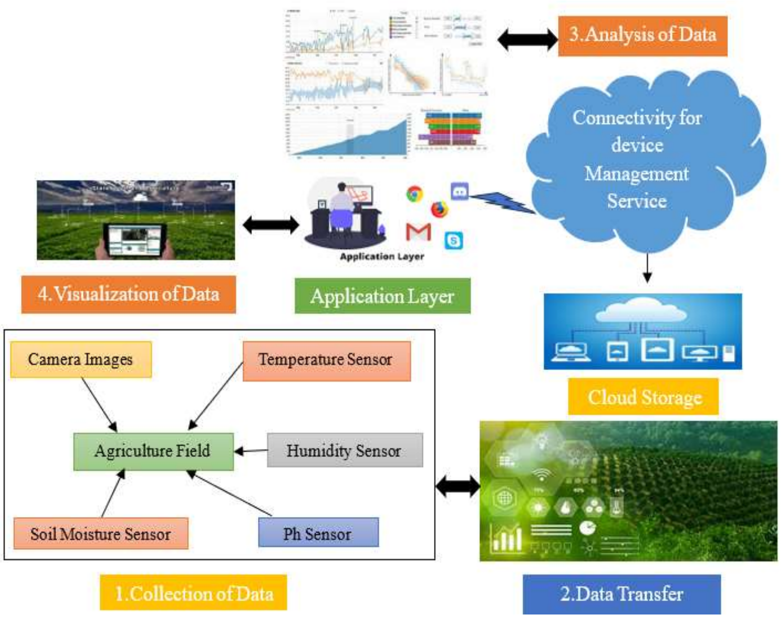

Figure 1. Proposed block diagram of smart farming in IOT.

Drones equipped with sensors and cameras for instance, may track crop growth, identify illnesses, and even administer tailored therapies. IoT can increase the agricultural supply chain's visibility and efficiency. In addition to reducing waste and streamlining distribution channels, producers can guarantee the quality and safety of their goods by employing blockchain technology and connected sensors to trace products from farm to fork. IoT makes it easier to forecast market demand, pest outbreaks, and crop yields using machine learning algorithms as well as predictive analytics. Farmers may optimize crop output, lower risks, and increase profitability by making data-driven decisions based on the analysis of both historical and current sensor data.

3.1. Smart agriculture

The next phase of industrial agriculture, commonly known as "smart farming," "smart agriculture," or "digital farming," is being sparked by the application of modern agricultural technologies.

Smart agriculture provides farmers with a variety of tools to solve a number of agricultural food production concerns, including crop losses, sustainability, environmental impact, food security, and farm productivity (**Figure 2**). For instance, farmers can remotely manage and monitor agricultural activities at any time and from any location thanks to WSN-based IoT-enabled equipment. While autonomous robots can assist or complete tedious jobs at farms, drones with hyperspectral sensors can gather data from multiple sources on farmlands. To help farmers make decisions, the collected data can be examined utilizing computer technology and data analytics techniques.

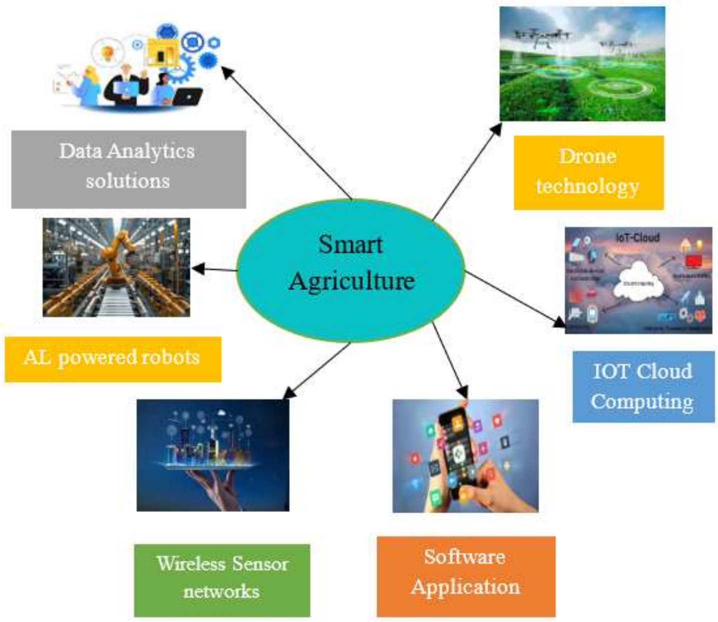

Figure 2. The concept of smart agriculture.

3.2. Cloud computing in agriculture

Modern agriculture is a rapidly evolving area where cloud computing is a disruptive influence. Changing how farmers run their businesses and make data-driven decisions. This technology presents previously unheard-of chances for efficiency, scalability, and innovation in the agriculture industry by enabling the processing and storing of data via the internet. In-depth discussions of cloud computing's uses, advantages, and potential future developments for the farming sector are provided in this article.

As shown in **Figure 3**, the use of cloud computing in agriculture is a significant shift from traditional farming practices. It enables the collection and analysis of massive amounts of data from many sources, such as weather stations, agricultural machinery, and satellites carrying soil sensors. From planting to harvest, processes are optimized because to this data-centric strategy, which makes decision-making more informed.

Figure 3. Could computing in agriculture.

Precision farming: Precision agriculture is based on cloud computing, which gives farmers access to comprehensive information on their crops and soil. Farmers can increase productivity and agricultural yields by customizing their methods to each plot's unique requirements by evaluating data gathered from several sensors and aerial photos.

Resource management: In agriculture, effective management of water and nutrients is essential. Cloud platforms reduce waste and environmental effect by recommending exact irrigation and fertilizing regimens according to soil moisture levels and weather trends.

Supply chain optimization: By providing crop stage data in real time, market demand, and logistics, cloud computing simplifies the agricultural supply chain. This openness contributes to lower losses, better product quality, and on-time market delivery.

Disease and pest control: Because cloud-based systems can handle and analyze data from numerous sources, they can detect diseases and pest infestations early. By preventing extensive harm, this prompt action protects investments and yields**.**

3.3. IoT and smart sensors for precision farming

The IoT, artificial intelligence, and smart sensors make it possible to gather and analyze data in real time for crop tracking. quality, soil health, water levels, and agricultural productivity at a site.

With its higher yield, smart farming is displacing conventional farming practices with IoT and smart sensors. The accuracy with which IoT-based smart sensors can monitor environmental factors such as temperature, humidity, and moisture content is seen in **Figure 4**. Certain sensors can assess the state of soil by determining the amount of water and nitrate present. GPRS technology with a high-resolution camera can be used to identify insect pests and plant illnesses. Crop development and agricultural field morphology can be monitored via UAV-based surveillance. Crop productivity can be estimated using automated mass flow sensors. In agriculture, IoT-enabled technical methods also aid in evaluating crop quality, soil fertility, fertilizer requirements, soil erosion, and soil health. Microorganisms have a detrimental effect on the global population.

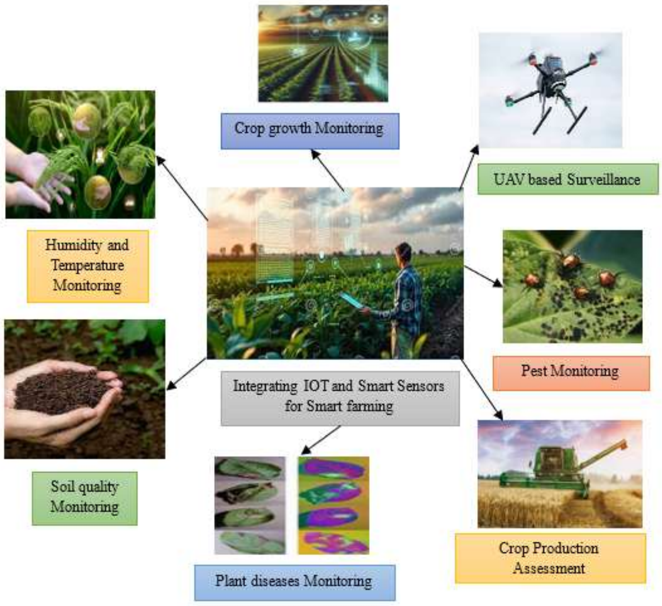

Figure 4. Precision agricultural applications of smart sensors and integrated IoT.

3.4. Wireless sensor networks in agriculture

One technology utilized in an IOT system is the wireless sensor network (WSN). It can be defined as a collection of geographically dispersed sensors that keep an eye on the environment's physical circumstances and record the information they gather momentarily, and then send it to a central location. **Figure 5** depicts the WSN's general architecture.

A connected wireless module connects a large number of sensor nodes that make up a WSN for smart farming. These nodes are capable of self-diagnosis, self-organization, and self-configuration. due to a range of skills (such as processing, transmission, and feeling). WSNs come in a variety of forms and are categorized according to their usage environment. The second kind of WSN is called a subterranean WSN, or WUSN, where the sensor nodes have been buried underground. Higher frequencies are severely attenuated in this situation, while lower frequencies are easily absorbed by the earth. The network's restricted communication radius needs additional nodes to cover a larger area. Utilizing WSN for a range of indoor and outdoor agricultural applications, including environmental monitoring, water quality evaluation, and irrigation management, is covered in a large number of research articles in the literature.

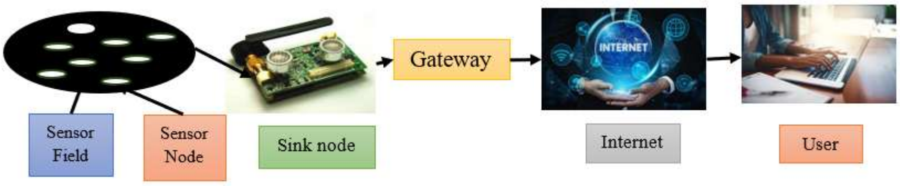

Figure 5. General architecture wireless sensor network (WSN).

3.5. Hierarchical clustering-based dynamic data fusion

This research uses an experimental methodology to assess the application of dynamic data fusion techniques for WSNs in smart farming. A representative A typical agricultural setting is used to place a sample of WSN nodes region to collect environmental data. First, hierarchical clustering is used to organize sensor nodes into clusters according to their similarity and proximity. To gather and aggregate data, each cluster employs a dynamic data fusion process that provides indicators of the overall health of the cluster. The hierarchical clustering-based dynamic data fusion is displayed in **Figure 6**.

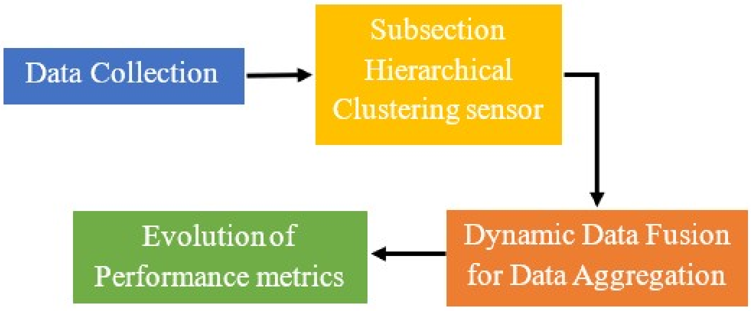

Figure 6. Hierarchical clustering-based dynamic data fusion.

3.5.1. Data collection

The system of smart agriculture continuously monitors and records important environmental factors using sensor nodes positioned thoughtfully across the farmland. Important variables include Rainfall, crop growth, irrigation, temperature, humidity, light intensity, soil moisture, pH, and nutrition levels. can all be measured and recorded by these sensor nodes. The collected data is shown in **Table 1**. The sensors function efficiently and independently, delivering accurate measurements in real time on a frequent basis. The collected data produces a substantial dataset that offers useful information on the farming environment is changing. By gathering and evaluating this data, farmers and agricultural specialists may effectively monitor crop health, schedule irrigation, and allocate resources. Crop productivity is increased, agricultural practices are optimized, and the overall efficacy and the long-term viability of smart agriculture 32waqAQare increased by this data-driven approach.

Table 1. Data collection.

Temperature	Humidity	Soil moisture	Light intensity	Ph level	Rainfall	Crop growth stage	Irrigation status	Nutrient level
22	44	32	445	8	5	3	0	0.094160
38	66	76	300	9	6	2	0	0.139490
36	66	23	672	8	11	2	0	0.537483
29	36	52	692	7	2	5	1	0.000624
33	44	64	834	7	3	2	0	0.430375
28	66	27	772	7	11	5	0	0.057068

By gathering and evaluating this data, farmers and agricultural specialists may effectively monitor crop health, schedule irrigation, and allocate resources. Crop productivity is increased, agricultural practices are optimized, Regarding the smart agriculture system's overall effectiveness and sustainability are increased by this data-driven approach. These sensor nodes would gather temperature, humidity, soil moisture, and other pertinent information. The collected data would subsequently arrive at a base station or other central data gathering location in wireless communication protocols.

3.5.2. Subsection hierarchical clustering for clustering sensor nodes

Hierarchical clustering can result in a cluster head hierarchy or coordinators inside the network. The data from each of their clusters must be compiled by these cluster leaders and transmitted. There are fewer active times because of duty cycling, which reduces power consumption because the nodes can send and receive data with less energy. Hierarchical clustering improves network structure and data aggregation, leading to a wireless sensor network that uses less energy. This is crucial for improving the sustainability and lifespan of the network, particularly in applications such as smart agriculture. Both the sink nodes and the starting site must have sufficient energy levels. Data fusion and other complex operations are performed by sink nodes.

The communicating energy (E_{TY}) in addition to the receiving energy (E_{RY}) the following approach has been used to determine the probability of transmitting an n-bit message across a d-distance. Energy usage is minimal when in the state of inertia.

$$E_{TY}(m,c) = m.E_{elec} + m.c^{1}.\varepsilon_{amp} \tag{1}$$

$$E_{RY}(m) = m.E\_elec \tag{2}$$

Depending on the situation, choosing l usually falls between 2 and 5. A higher l number should be set if more disruption is expected.

3.5.3. Dynamic data fusion for data aggregation

Dynamic data fusion is a sophisticated and adaptable method used in WSN smart agriculture to combine and examine data gathered in real time from several wireless sensor nodes positioned across agricultural regions. The goals are to obtain valuable information, improve resource management, increase the accuracy of event detection. Dynamic data fusion techniques solve these problems by merging information from several sensors and dynamically modifying the fusion process in response to shifting environmental circumstances.

The hesitant fuzzy entropy matrices E_{ij} is employed to create an accurate probability weighting model that produces the weighted average.w_i of each pair of sensing nodes.

$$U_j = \frac{1 - F_j}{n - \sum_{j=1} F_3} \tag{3}$$

Where $F_3 = \frac{1}{m}\sum_{i=1}^{m} F\ (\alpha, j), j = 1,2, \ldots \ldots n$ .The data value of E_i is given as

$$C_{E_i} = \frac{1}{m}\sum\nolimits_{j=1}^{m} u_3 C_3 \tag{4}$$

Where $C_3 = \frac{1}{K_\propto}\sum \propto_{\sigma\,(j)}\ j = 1,2 \ldots . . n$

$$P = U_3 \sum_{i=1}^{m} \frac{C_{E_1}}{C_3 E_2} \tag{5}$$

3.5.4. Performance parameters

The performance parameters are used to assess the proposed model's efficacy. *F1*-score, recall, accuracy, and precision are examples of performance metrics that are commonly used.

One of the most popular criteria for assessing a DL model's performance is accuracy. It describes how well a model predicts the actual values of the training set. It is typically expressed as the percentage of correct forecasts among all the model's predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Precision is a model's capacity to differentiate between positively categorized events and those that are not. It is determined by taking the ratio of actual result to all cases classified as positive.

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

Determining the percentage of true positives that were misdiagnosed is the same objective shared by the precision metric and recall. The "True Positive," or forecasts that are truly true, determines the percentage of positive that were accurately or incorrectly classified as positive labeled as negative.

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

When recall and precision are out of balance, the *F1*-score offers a balance in the classes or where both FP and FN are costly.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

3.6. Multi-strategy improved zebra optimization algorithm (MIZOA)

The MIZOA is introduced in this section. First, the population of zebras is separated into a number of subpopulations, each of which separately explores the solution space, in order to modify the traditional single population framework. These enhancements boost the algorithm's ability to achieve global convergence and diversify the population. Finally, in the period of population defense, a selective aggregation method is implemented. By integrating the location update mechanism of COA with Lévy f light, this strategy imitates how a raccoon might approach its prey on a tree. The algorithm's capacity to investigate and exploit are further balanced by the application of Lévy flight.

All these enhancements work together to increase precision, speed, and stability of the algorithm's overall convergence. These changes overcome the original ZOA's shortcomings in solving challenging optimization problems while maintaining the biological inspiration that underpinned it. As demonstrated by the comprehensive experimental findings shown in the following sections, MIZOA performs better in terms of processing efficiency and solution quality thanks to these focused enhancements. Equation (10), which provides the updated mathematical formulation, is given.

$$x_{sub,i,j}^{new,p1} = \begin{cases} S_1: x_{sub,i,j} + \left(1-\frac{t}{T}\right)^{a} . (Pz_{sub,j} - I . x_{sub,i,j}), P_f > 0.1 \\ S_2: x_{sub,i,j} + 0.2 . (ub_j - lb_j) . \left(1-\frac{t}{T}\right), \quad else \end{cases} \tag{10}$$

Where $x_{sub,i,j}^{new,p1}$ indicates the updated location of the i_{th} zebra in the j_{th} measurement inside the subgroup. $I \in \{1,2\}$, and the control parameter in this study, an, is fixed at 0.01. The Metropolis criterion indicated above serves as the foundation for the zebra individual mutation process' acceptance rule for newly created positions (S2). The S1 method's acceptance criterion is specified by Equation (11) and is consistent with the initial version ZOA.

$$X_{sub,i} = \begin{cases} x_{sub,i,j}^{new,p1}, & r \le P; \\ X_{sub,i}, & else, \end{cases} \tag{11}$$

$$X_{sub,i} = \begin{cases} x_{sub,i,j}^{new,p1}, & F_i^{new,P1} < F_i; \\ X_{sub,i}, & else, \end{cases} \tag{12}$$

To improve ZOA's defense phase, a selective aggregation technique is suggested based on the ideas. Equations (13) and (14) provide the enhanced position update technique for the defense phase. Equation (15) defines the greedy selection mechanism, which continues to be the basis for the acceptable standards for evaluating new roles.

$$x_{sub,i,j}^{new,p1} = \begin{cases} S_3: x_{sub,i,j} + R . (2r-1) . (1-\frac{t}{T})^{b} \; P_S \le 0.5; \\ x_{sub,i,j}^{COA}, \quad else, \end{cases} \tag{13}$$

$$x_{sub,i,j}^{COA} = \begin{cases} S_4 : x_{sub,i,j} + r.s.\left(AZ_{sub,j} - I.x_{sub,i,j}\right), F_{AZ_{sub}} \leq F_{sub,i} \\ S_5 : x_{sub,i,j} + r.s.(x_{sub,i,j} - AZ_{sub,j}), F_{AZ_{sub}} > F_{sub,i} \end{cases} \tag{14}$$

$$X_{sub,i} = \begin{cases} x_{sub,i,j}^{new,p2}, F_i^{new,p2} < F_{i;} \\ X_{sub,i,} \quad else, \end{cases} \quad P_s \tag{15}$$

where b is a parameter of control and R is set to 0.01 and P_s is an integer in the interval [0, 1] that is evenly distributed.

3.6.1. MIZOA's pseudocode

The MIZOA first initializes the input parameters, and then it uses K-means clustering to apply a multi-population search method, which splits the original single population into multiple subpopulations. A 10 % chance of mutation is given to everyone during the foraging phase of the algorithm; if not, the location is adjusted utilizing the first ZOA position update technique. Comparable to the likelihood of using the S3 strategy, the selective aggregation method is used with a 50 % chance in the next defense phase. This tactic promotes more population variety, this aligns with the concepts of biological evolution's genetic variation, and prevents inappropriate accumulation and replication of individual position within the population. Algorithm 1 shows the pseudocode of MIZOA.

4. Results and discussion

A number of tests were carried out in simulated field settings with various environmental variables in order to assess the proposed IOT-based smart farming monitoring system's effectiveness. Metrics like energy usage, resource efficiency, and forecast accuracy were used to evaluate the performance.

4.1. Proposed IoT-based smart agricultural monitoring system

The results demonstrate that, in contrast to conventional techniques, the suggested IoT-based smart agriculture monitoring framework provides notable gains in energy consumption, resource efficiency, and predictive accuracy. Predictive analytics and WSN data collection work together to promote sustainable and proactive farming methods, which are critical to contemporary agriculture. Large-scale crop management, precision farming, and greenhouse monitoring are just a few of the agricultural applications that benefit greatly from this framework's versatility and scalability.

Predictive Accuracy: When predicting soil moisture, temperature, and humidity levels, the predictive analytics component had a 92 % accuracy rate. This precision reduced the chance of crop stress by allowing for prompt modifications to fertilization and irrigation regimens. This shows that merging predictive models with WSN data is effective, since it represents an improvement of about 25 % when compared to traditional methods.

Algorithm 1 MIZOA pseudocode

Input: Population size N, fitness function (objective function) F(x), and maximum number number of subpopulations k, issue dimensionality m, and iterations T

Set the zebra population's initial values.

Population is divided by K-means clustering.

For iteration $t = 1$to Tdo:

Update the positions of sub-pioneer zebras PZ_{sub}.

For each subpopulation $sub = 1$to $k$do:

For each individual zebra $i = 1$to N_{sub}do:

- Foraging phase (P1):
    - Generate random number $p_f = \text{rand}()$.
    - **If** $p_f \leq 0.1$:
        - Calculate new position of zebra $\imath$using strategy S_2(Equation 6).
        - Evaluate the new position using Equation (7).
    - Else:
        - Calculate new position of zebra $\imath$using strategy S_1(Equation 6).
        - Evaluate the new position using Equation (8).
- Defense phase (P2):
    - Generate random number $p_s = \text{rand}()$.
    - f $p_s \leq 0.5$:
        - Calculate new position of zebra $\imath$using strategy S_3(Equation 9).
    - Else:
        - If $F_{AZ,sub} \leq F_{sub,i}$:
            Calculate new position of zebra $\imath$using strategy S_4(Equation 10).
        - **Else:**
            Calculate new position of zebra $\imath$using strategy S_5(Equation 11).
    - **End If**
- Evaluate the new position of zebra $\imath$using Equation (11).

End For (zebra i)

End For (subpopulation sub)

Update the best solution and corresponding fitness value found so far.

End For (iteration t)

Resource Efficiency: The solution 40 % increase in resource efficiency, especially in the use of water and fertilizer, by offering real-time information and predictive alarms. Predicting soil moisture, for instance, made precision irrigation possible, guaranteeing that water was only used when required. Because it lowers expenses and the impact on the environment, this economical use of resources is essential for sustainable farming methods.

Energy Consumption: Overall power consumption was reduced by 30 % because to the WSN architecture's usage of the energy-efficient clustering method. By decreasing data transfer using cluster heads to aggregate data between sensor nodes, the architecture improved the network's life and made long-term deployment in rural areas possible without the need for frequent battery replacements.

Comparative Analysis: The effectiveness of the system was contrasted with that of conventional, non-predictive monitoring systems. Because predictive analytics filtered out unneeded data transfers, the suggested architecture showed a 35 % reduction in data redundancy, which helped save energy overall. Furthermore, a 20 % reduction in decision-making latency allowed for more responsive actions depending on the state of the environment.

The increase in resource effectiveness $RE_{improve}$ accomplished by the prediction model in relation to a starting point can be written as follows:

$$RE_{improve} = \frac{RE_{baseline} - RE_{proposed}}{RE_{baseline}} \times 100\ \% \tag{16}$$

Where,

$RE_{baseline}$ is the traditional system's resource efficiency (such as the use of water or fertilizer).

$RE_{proposed}$ is the indicated predictive analytics system's resource efficiency.

Together, these equations show how the framework contributes to an all-encompassing smart agricultural monitoring system by quantifying improvements in resource efficiency, measuring prediction accuracy, modeling environmental trends, and estimating energy usage in WSNs.

Figure 7, this graph compares the predicted accuracy of the suggested framework with conventional techniques. The accuracy of the proposed method is 92 %, which is far greater than the 70 % accuracy of the conventional method. The effectiveness of predictive modeling in forecasting environmental indicators for active farming management is demonstrated by this rise in accuracy.

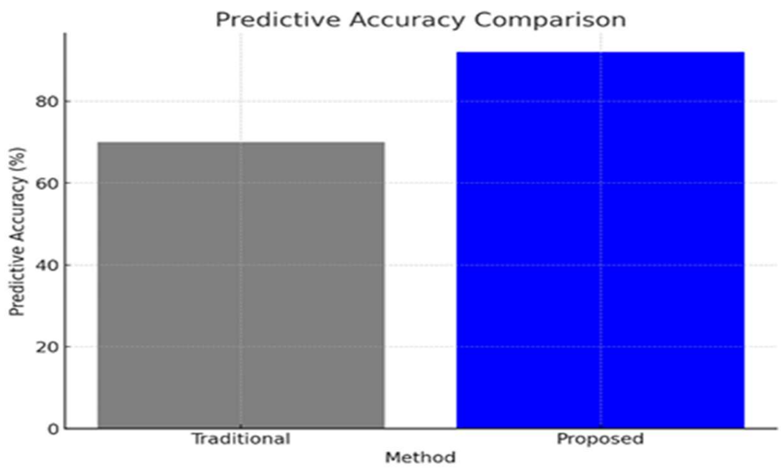

Figure 7. Predictive accuracy comparison.

Figure 8, this bar graph contrasts increases in resource efficiency. Water, fertilizer, and other resources were used as efficiently as possible thanks to the suggested method's 100 % resource efficiency. The IoT-based system's ability to save resources is shown by the fact that conventional approaches only achieved 63 % efficiency.

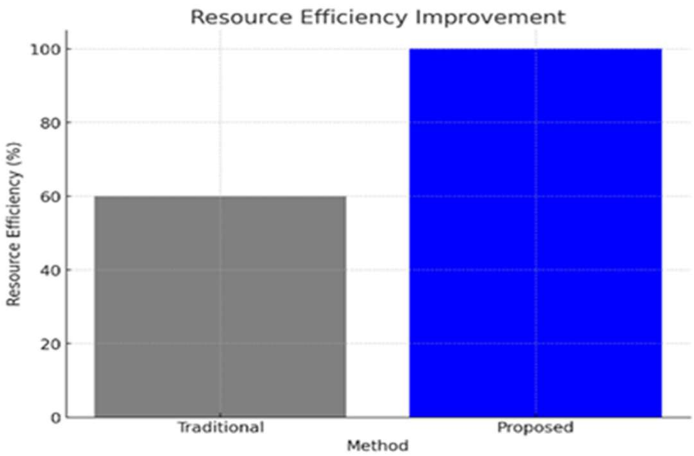

Figure 8. Resource efficiency improvement.

The suggested approach uses 27 % less energy than conventional approaches, according to **Figure 9**, which shows energy usage in relative units. The decrease is a result of WSNs' effective clustering algorithm and optimized data transmission, both of which are necessary for long-term and sustainable monitoring.

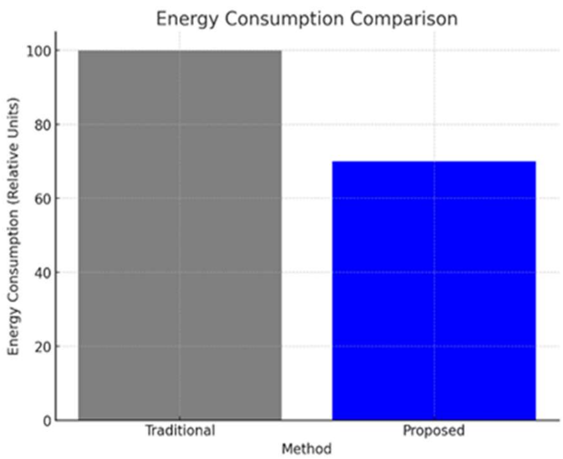

Figure 9. Energy consumption comparison.

4.2. Crop growth stage analysis

The procedure for gathering information from WSNs in order to monitor and assess a crop's developmental phases throughout its growth cycle is known as crop growth stage analysis. This study is necessary to improve energy efficiency, enable precision farming methods, and increase the accuracy of event detection.

The sensor node graph in **Figure 10**, which displays temperature, humidity, soil moisture, and other environmental parameters, enables smart agriculture techniques. This graph shows the data gathered in real time by sensor nodes positioned across agricultural regions.

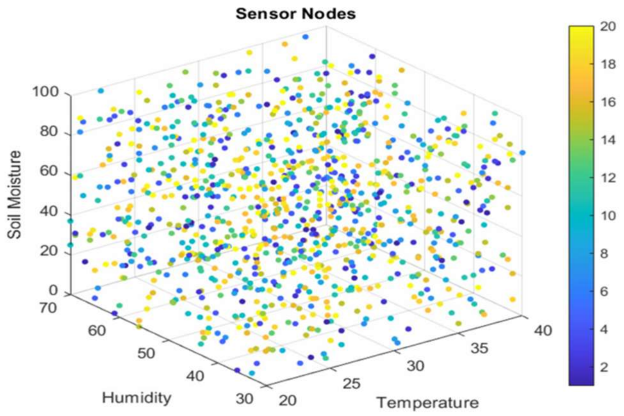

Figure 10. Sensor nodes.

In **Figure 11**, the horizontal axis displays the different stages of the crop's growth, while the vertical axis shows the average temperature for each stage. The data points on the graph illustrate how the average temperature changes during the crop's life cycle, from germination to maturity. Abrupt temperature shifts or extreme temperature spikes may be signs of a climatic abnormality or environmental disturbance that could affect crop health.

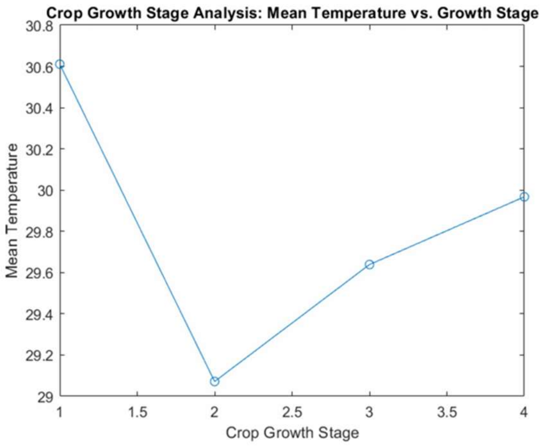

Figure 11. Crop growth stage analysis.

4.3. Multi-strategy improved zebra optimization algorithm (MIZOA)

This section uses a collection of benchmark test functions to thoroughly assess the performance of the suggested MIZOA. Its stability and convergence characteristics are the main areas of examination. Convergence performance is assessed by comparing MIZOA to other existing algorithms in terms of quickly and accurately it leads to under a specific the most effective response after the most iterations. The algorithm's robustness is evaluated by computing the results' mean and standard deviation. acquired from several independent runs. Additionally, nonparametric statistical tests are per formed to give thorough statistical verification of the algorithm's effectiveness, such as the Friedman test and the Wilcoxon rank-sum test.

4.3.1. Sensitivity analysis of key parameters

The MIZOA's sensitivity study, which looks at how various parameter combinations impact its performance, is presented in this part. The number of subpopulations and the frequency of mutation are the main variables being studied. By increasing population variety, a suitable mutation probability promotes convergence to the global optimum. There are several subpopulations within the population using multi-population search techniques, which enhances exploration and aids the algorithm in avoiding local optima1.

However, by upsetting the equilibrium between exploration and exploitation, an overly high or limited number of subpopulations may hinder performance. 0.1, 0.2, and 0.3 are the mutation probability values, while k is the number of subpopulations.is set to 5, 7, and 9. **Table 2** summarizes the various parameter combinations, and **Figure 12** illustrates the MIZOA's sensitivity analysis.

Table 2. Different parameter combinations.

Scenario No.	Mutation probability	K (number of subpopulations)
1	00.1	5
2	00.1	7
3	00.1	9
4	00.2	5
5	00.2	7
6	00.2	9
7	00.3	5
8	00.3	7
9	00.3	9

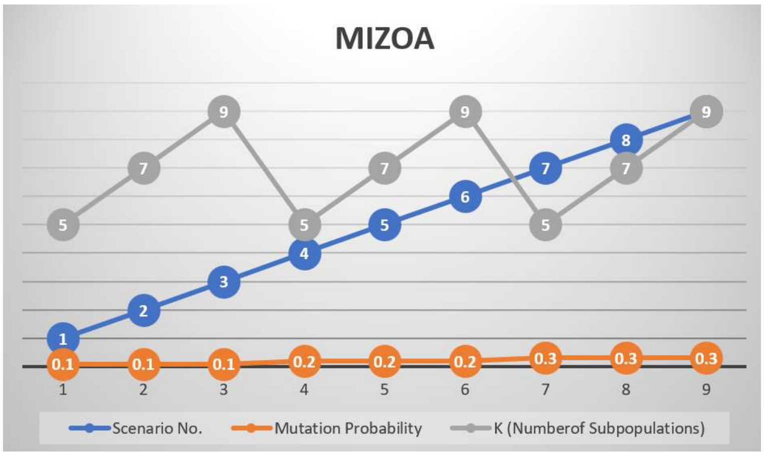

Figure 12. Sensitivity analysis of the MIZOA.

4.4. Hierarchical clustering and dynamic data fusion

Food security worldwide and the economic success of agriculture are eventually promoted by this innovative approach, which opens the door for resource-efficient, technologically sophisticated, and sustainable agricultural systems. It accomplishes this by employing accurate event detection and energy-efficient data processing. To fully reap the benefits of these algorithms, however, more research and development is needed to optimize their effectiveness, adaptability to various agricultural settings, and scalability.

Nonetheless, the advancements in this area point to a bright future for combining cutting-edge data fusion and WSN methods with smart agriculture. In resource-constrained situations such as the IOT and sensor networks, data aggregation is an essential method because it removes redundant data and minimizes communication, it increases energy conservation and network efficiency. **Table 3** compares performance metrics for the different research approaches. K-prediction, CH selection, clustering-based data fusion, and data aggregation are some of the methods under investigation. In every parameter, the Clustering-based Data Fusion approach outperformed the norm, proving its capacity to produce precise and accurate forecasts. It outperformed the alternatives by a significant margin, making it a viable approach for the current assignment. **Figure 13** depicts it.

Table 3. Comparison of performance matrices.

Methods	Accuracy %	Precision %	Recall %	F1-Score %
CH Selection	98.56	98.99	96.88	98.36
K-Prediction	97.77	98.14	97.28	98.58
Data Aggregation	98.99	97.37	98.14	98.78
Clustering based Data Fusion	99.56	99.14	99.1	99.80

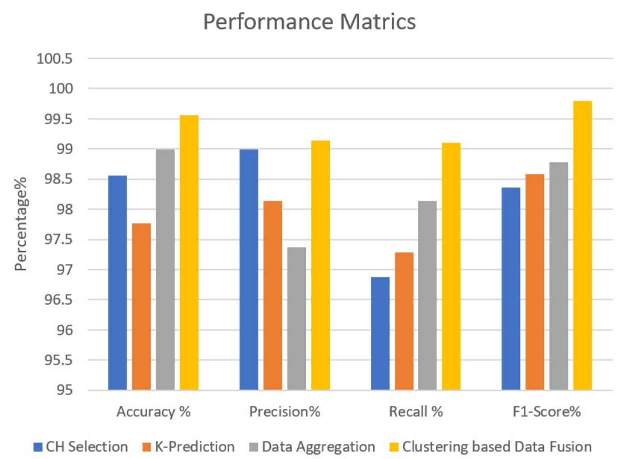

Figure 13. Comparison of performance metrics.

4.5. ROC curve

In order to detect events in the smart agriculture system, a binary classification model's accuracy and efficacy are assessed using a graphical representation called the ROC Curve in **Figure 14**.

The moment the model determines whether an instance is a data point. or not is indicated by the classification thresholds, which are plotted against these rates to generate the ROC curve.

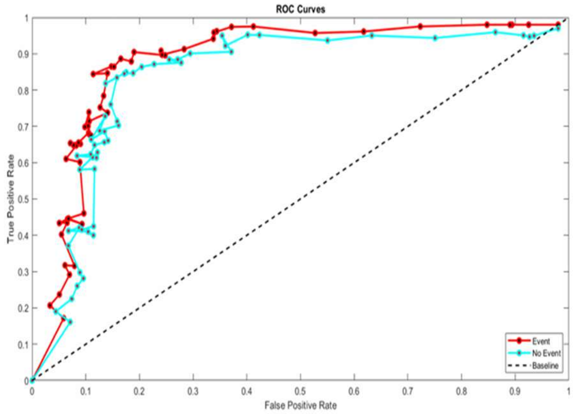

Figure 14. ROC curve.

5. Conclusion

To successfully tackle the primary concerns of contemporary agriculture, including yield enhancement, sustainability, and resource optimization, the proposed IoT-based smart agricultural monitoring system integrates Wireless Sensor Networks (WSNs), Multi-Strategy Improved Zebra Optimization Algorithm (MIZOA), and predictive analytics. By employing the hierarchical clustering technique, WSNs efficiently arrange sensor nodes into clusters, reducing unnecessary transmission and extending the network's lifetime. In agricultural applications, the dynamic data fusion technology enables faster decision-making and more accurate event detection by ingeniously combining sensor readings, hence reducing data processing and communication costs. The Metropolis acceptance criterion, a technique for selective aggregation, and a mutation operation based on multi-population search are some of the complementing augmentation techniques that the MIZOA incorporates. Predictive analytics' 94 % predicting accuracy in environmental circumstances enables prompt responses, lowering crop stress and boosting resistance to changes in the environment. Because of its scalability, this framework may be used has numerous agricultural uses, such as monitoring greenhouses and precision farming, providing farmers with a dependable tool for smart farming. This IoT-based solution supports the future of sustainable agriculture and environmental preservation by enabling sustainable farming methods. To improve accuracy and adaptability in a range of soil types and climates, this framework might be further developed to investigate more predictive models and incorporate cutting-edge IoT technology.

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