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Multi-objective Clustering Framework for Energy-efficient Precision Agriculture in WSNs using Optimized Convolutional Autoencoder with Dual-key Transformer Network

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Abstract: Precision agriculture relies on wireless sensor networks (WSNs) to support informed decision-making, thereby enhancing crop yields and resource management. A critical challenge in such networks is minimizing the energy consumption of sensor nodes while ensuring reliable data transmission. Sensor nodes are grouped using an optimal multi-objective clustering approach, which also chooses appropriate cluster heads (CH) for effective communication. By combining the exploration power of the Osprey Optimization Algorithm with the exploitation power of the Parrot Optimizer, a hybrid optimization approach improves CH selection. A hybrid deep learning framework, combining a convolutional autoencoder with a dual-key transformer network, is designed to monitor energy utilization and detect constraints affecting consumption. Training and testing performance of this framework is further improved using a metaheuristic based on the cooperative feeding and locomotion behavior of gooseneck barnacles. Experimental evaluation demonstrates superior performance, achieving 99.2% accuracy, 68 kbps throughput, 98% packet delivery ratio, and a network lifetime of 85 ms. With an average delay of 0.23 seconds, energy consumption is decreased to 39 J, demonstrating the effectiveness of the suggested strategy for dependable and sustainable precision agriculture applications.

Index Terms: Wireless Sensor Networks (WSNs), Precision Agriculture, Multi-Objective Clustering, Cluster Head (CH), Osprey Optimization Algorithm (OOA).

1. Introduction

The application of WSN can be very important to precision agriculture in terms of energy conservation [1]. A management technique used in the agricultural production process is precision agriculture. It makes reasonable use of information technology and consistently raises the standard and yield of crop production [2]. Additionally, it lessens the amount of resources and energy waste as well as pollution to the environment. It enhances the modernization and precision [3]. Currently, several issues, including varying conditions, unfavorable working environments, inadequate power supplies, and limited service lives, limit the use of agricultural sensors. Additionally, there is a lack of data infrastructure and public communication due to the agricultural manufacturing base's remote location from the city, and specialist communication techniques are costly. There may be problems with distortion and spectrum compatibility [4].

The sustainable growth of agriculture and food production-based economies is positively impacted by the effective use of wireless sensor networks in the farming sector. The ecology also benefits from the results of these activities [5]. Accurate assessment of the physiological state of crops is made possible by ecological and agronomic monitoring mechanisms, which are crucial for timely agrotechnical system changes aimed at mitigating the effects of climate change on agricultural productivity [6]. WSNs are used to evaluate water and irrigation system performance, as well as temperature and environmental conditions, in agricultural practices [7]. WSNs facilitate the large-scale production of crops by the farmers. Note, however, that sensor nodes require a source of power to operate [8]. These networks directly impact the economy, making crops more productive and efficient [9]. An excellent method of realizing precision agriculture, increasing the food crop yields, and lowering the workloads of farmers is the application of WSNs in the agricultural sector [10].

Precision farming requires crops to grow properly, and this leads to the importance of WSN. It can achieve successful green precision farming, lessening the dependency on pesticides, and controlling weeds and pests [11]. To provide users with quick feedback, WSN can sense and gather data in real-time on various changes in the agricultural production process. The outcomes of data processing and evaluation are provided to users, enabling them to carry out efficient precision agriculture management [12].

For efficient energy utilization in WSNs, clustering is a useful technique. After choosing the best CH for the cluster, nodes can coordinate communication by sending data to a central node or sink [13]. The CH increases the network lifetime by promoting cooperation between the cluster and central server and reducing energy consumption related to communication overhead [14]. To extend the network's lifespan, various optimization techniques have suggested using CH selection; however, due to their lengthy convergence times, none of the current algorithms for CH selection are feasible [15]. Therefore, a hybrid meta-heuristic optimization approach is employed for optimal CH selection with reduced complexity and rapid convergence. Additionally, by achieving high classification accuracy and thereby increasing network capacity, the inclusion of the Deep Learning (DL) model enhances the effectiveness of the strategy being employed. The major advancements in the proposed research work are listed below:

- A novel multi-objective clustering-based energy utilization detection for precision agriculture is developed using an optimized DL model.
- Initially, a new hybrid optimization approach is introduced for performing optimal CH selection by integrating the Osprey Optimization Algorithm (OOA) with Parrot Optimizer (PO).
- Secondly, a hybrid DL model is developed by combining Convolutional Autoencoder Network (CAEnet) and Dual-Key Transformer Network (Dktnet) for detecting the energy utilization and factors that affect the energy usage.
- With the aid of GBO, the CAE-DktNet hyperparameters are tuned. An innovative meta-heuristic optimization method inspired by the feeding and movement patterns of the gooseneck barnacle is the proposed GBO algorithm.
- The algorithm mimics their swarm intelligence, where individuals cooperate to optimize their positions in response to environmental conditions and food sources.
- Finally, several performance evaluation metrics are used to assess the effectiveness of the proposed approach.

The remaining portions of this study are arranged as follows: A few research studies that are relevant to the study idea are covered in Section 2. In Section 3, the suggested methodology is briefly summarized. Simulation results and commentary are presented in Section 4. Potential directions for further research are discussed in Section 5, which wraps up the presented research effort.

2. Related Works

Some of the recent literature reviews related to the presented study are described below:

Pandiyaraju, V., et al. in 2023 [16] introduced a new multi-objective node organizing method for WSN sensor nodes. To improve the choice of CH in WSNs, an Election-based Aquila Optimizer (EAO) was proposed as a new multi-objective hybrid optimization method. EAO unites EBOA and AO to guarantee the optimal choice of CH. Moreover, the proposed approach utilizes an Optimized Convolutional Neural Network (O-CNN) and a recently devised optimization plan, which is expected to enhance the accuracy of training, testing, and the clustering algorithm.

Dey, et al. in 2024 [17] presented an Energy-aware data routing system based on deep Q-networks (DQNs) that sends information to the sink node of the WSNs. An agricultural field was used to capture soil moisture data at multiple depths, which were then transmitted to an aggregator node. To produce low-power, accurately correlated data, the data was aggregated using principal component analysis. Lastly, an energy-efficient route utilizes the sink nodes to transmit the combined data of the merged nodes to the network gateway. The suggested DQN-based routing method stores the Q-values of various state-action pairings in the Q-table.

Asha, A., et al. in 2023 [18] developed an IoT system to establish a WSN specifically designed for services provided by smart cities. The suggested approach uses advanced intelligence algorithms to categorize the network's performance as best as possible. An Optimal Recurrent Neural Network (ORNN) receives the outputs from each wireless network to predict the overall performance of the Internet of Things network. SA-HBA was used in this technique to adjust the ORNN parameters. Various parameters, including energy consumption, mobility, data volume gathered and transmitted, throughput, packet loss, false positives, and latency, are used to assess the efficiency of each network.

Debasis, et al. in 2023 [19] introduced an Energy-Efficient Clustering Algorithm (EECA) that minimizes the amount of sensor node energy consumed to extend the WSN lifespan. The EECA target area is perceived as a cluster of smaller territories. An Artificial Neural Network (ANN) selects CH of the presented model on a single node per area. The sensor nodes with the minimum energy threshold as required can be allowed to enter the CH selection phase. The sensor node that is the best scored is the one that was selected to act as the CH of its region.

Kumar, et al. in 2023 [20] developed a DCNN architecture that predicts soil moisture, helping farmers optimize irrigation through precision agriculture to boost crop yield with limited water consumption. The proposed strategy would help sustain crop production and ensure an efficient balance of water consumption by conserving water resources for future irrigation use. The input and storage data formats suitable for Apriori and Gated Recurrent Unit (GRU) models are presented in grid views. The system developed employs sensor technologies and parameter estimation to forecast irrigation demand, facilitating the optimization of irrigation planning in accordance with real needs.

Kumar, Amandeep, et al. in 2023 [21] introduced a cross-layer hybrid Particle Swarm Wild Horse Optimizer (PSWHO) and a resilient routing technique (CL-HPWSR). To address the problem of excessive power consumption in WSNs, the hybrid PSWHO optimization technique was employed to develop a cross-layer-based optimal CH selection algorithm. A complex routing architecture called the EDGENN, which was utilized to identify the most effective data transmission paths, was also introduced by the analysis.

Ghamry, et al. in 2024 [22] suggested multi-objective intelligent clustering-based routing system that optimizes IoT-enabling WSNs via deep reinforcement learning. The proposed approach aims to address low throughput, large communication delays, and a shorter network lifespan. It divides the total network into a few disproportionate clusters, according to the load of real-time data on sensor nodes, and thus avoids a premature network breakdown. Additionally, an unequal clustering strategy is employed to allocate energy consumption more evenly across and within clusters.

2.1. Problem Statement

One of the primary challenges in precision agriculture is believed to be the efficient use of energy by various sensor nodes in WSNs. For WSNs, the traditional Machine Learning (ML) method for maximizing energy use in precision agriculture leads to a large computational overhead and has poor classification accuracy. The network's total lifespan may also be shortened by frequent data transmission for ML model updates, which could drain the energy of sensor nodes.

2.2. Motivation

O-CNN [16], DQN [17], O-RNN [18], ANN [19], DCNN [20], EDGENN [21], and DRL [22] are some of the existing methods for energy management in WSNs for precision agriculture that show notable improvements in clustering, routing, and feature extraction. Nonetheless, several restrictions still remain. Classification is the main goal of O-CNN and ANN-based techniques, which do not specifically optimize CH selection for energy efficiency. Although they have a large computational overhead and can quickly drain the energy of sensor nodes, DQN and DRL enhance routing decisions. EDGENN enhances cross-layer optimization but does not jointly address energy utilization, detection accuracy, and hyperparameter tuning. To address these gaps, the proposed work employs a novel clustering technique based on multi-objective optimization to select optimal CHs that satisfy various objective constraints and categorize sensor nodes into discrete, non-overlapping clusters. Through the effective transfer of real-time environmental data from sensor nodes to the base station made possible by this integrated strategy, precision agricultural WSNs can operate with low latency, accuracy, and energy efficiency.

3. Proposed Methodology

By combining sensor nodes into intra- and inter-clusters and selecting the optimal CHs for secure data transmission, the suggested framework achieves efficient energy usage in WSN for precision agriculture through multi-objective clustering. Utilizing the Parrot Optimizer's local exploitation capabilities and the Osprey Optimization

Algorithm's global exploration capability, the Osprey Parrot Optimization Algorithm (OPOA) is used in CH selection to achieve balanced and energy-efficient clusters. For identifying energy usage patterns and determining constraints influencing consumption, a hybrid deep neural network model, the Convolutional Autoencoder with Dual-Key Transformer Network (CAE-DktNet), is utilized, integrating feature extraction with strong sequential learning capabilities. The Gooseneck Barnacle Optimization (GBO) algorithm then further optimizes the process by fine-tuning the hyperparameters of CAE-DktNet for stable training, high accuracy, and preventing overfitting. By incorporating these three complementary methods, the framework addresses clustering, detection, and optimization collectively, thereby enhancing energy efficiency, reliability, and sustainability in precision agriculture. The parameters are derived from typical WSN energy models to make them practical in the actual world. These parameters include transmission energy (50 nJ/bit), electronic energy (5 nJ/bit), free-space amplification energy (10 pJ/bit/m2), and maximum communication range (100 m). These limitations represent real-world implementation constraints, such as low battery capacity, environmental noise, and hardware-dependent consumption rates. The energy utilization detection block schematic of precision agriculture by WSNs is shown below in Figure 1.

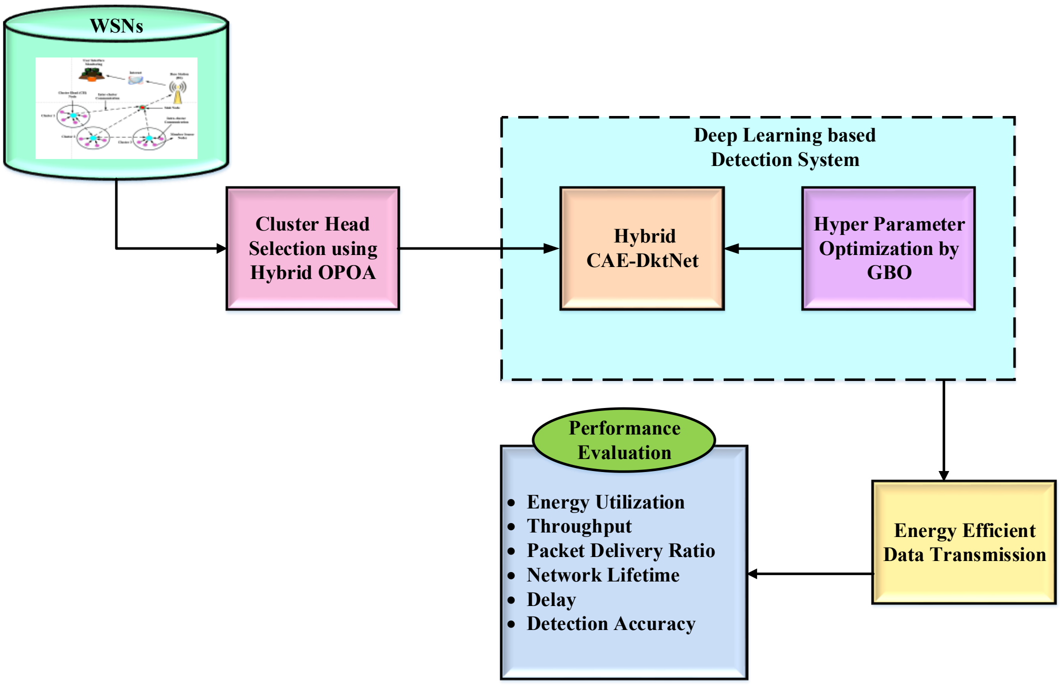

Fig.1. Block schematic of energy utilization detection for precision agriculture

The WSN consists of many member sensor nodes dispersed randomly throughout a given region, as well as a sink node. When a sink node is installed in an agricultural farm, the network's member sensor nodes are aware of its location. When the network first starts up, every node has the same amount of energy available to send information to the base station. The DL architecture used in the suggested study aids in detecting energy use and variables influencing energy consumption. These real-time data are captured by the WSN sensors to optimize energy usage and improve crop management.

3.1. Selection of Optimal CH based on Multi-objective Clustering and Hybrid Optimization

A significant obstacle in precision agriculture is the effective use of energy by sensor nodes in WSNs. This leads to the presentation of a multi-objective clustering technique to categorize WSN sensor nodes into numerous distinct, non-overlapping groups. The process of clustering in WSNs for precision agriculture is demonstrated below in Figure 2:

A WSN consists of clusters of nodes, each cluster being controlled by a node, called a CH. It is the task of this node to communicate with all sensors in its cluster and with other clusters. Due to its importance, the CH requires a selection process. The best CH node from the available sensor nodes in the cluster is identified in the proposed research study using a hybrid multi-objective optimization approach. The suggested method hybridizes OOA and PO to determine the best CH, considering several factors, including the shortest latency, the least energy consumption, and the optimal distance between and within clusters.

It is essential to appoint the right CH to each cluster for several reasons. Firstly, it reduces the number of nodes required to transmit data directly to the base station, thereby saving energy that is essential in settings with limited resources. Second, the optimal CH option ensures that data is collected on all field regions, which increases network coverage. Lastly, by optimizing energy efficiency and ensuring that nodes operate without difficulty, it is used to extend the overall network lifetime. That is why it is essential to select the most suitable CH to manage data transmission within the cluster. A new meta-heuristic optimization technique is the hybrid Osprey Parrot Optimization (OPOA) technique, which combines OOA and PO. In this case, the PO is driven by the foraging behavior, communication, staying put, and fear of stranger's characteristics of parrots Pyrrhura Molinae, and the OOA is driven by the hunting behavior of ospreys. The following is the procedure for the proposed HOPOA:

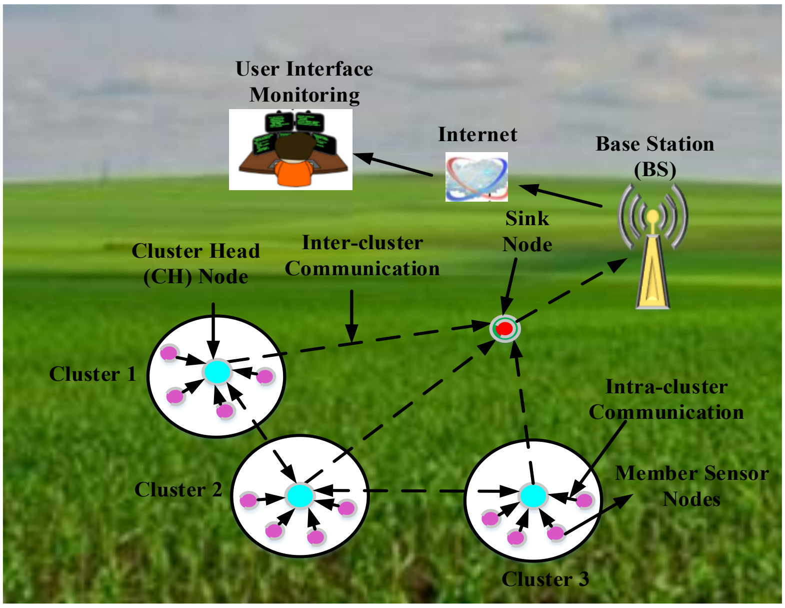

Fig.2. Multi-objective clustering in precision agriculture WSN showing intra- and inter-cluster formations

Step 1: Initialization

Initialization entails setting the maximum number of iterations, upper and lower bounds, and population size. Moreover, search agents are randomly assigned to their locations within the search space. The initialization procedure is represented by the model,

$$U = \begin{bmatrix} U_1 \\ \vdots \\ U_i \\ \vdots \\ U_{N_P} \end{bmatrix}_{N_P \times h} = \begin{bmatrix} u_{1,1} \cdots u_{1,j} \cdots u_{1,h} \\ \vdots \ddots \vdots \iddots \vdots \\ u_{i,1} \cdots u_{i,j} \cdots u_{i,h} \\ \vdots \iddots \vdots \ddots \vdots \\ u_{N_P,1} \cdots u_{N_P,j} \cdots u_{N_P,h} \end{bmatrix}_{N_P \times h} \tag{1}$$

$$u_{i,j} = LB_j + k_{i,j} \cdot (UB_j - LB_j), i = 1,2,\ldots\ldots, N_P, j = 1,2,\ldots\ldots, h \tag{2}$$

where, $u_{i,j}$ represents the i^{th} candidate solution in j^{th} dimension, N_p denotes total search agent counts in search space and $k_{i,j}$ signifies random number between [0, 1].

Step 2: Calculation of fitness function

The objective function measurement of every possible solution is evaluated to identify the best candidate solution. Several multi-objective characteristics, including energy consumption, intra-cluster distance, and latency, are considered to identify the best CH node for each cluster based on a fitness function. To enable effective data transfer, the optimal CHs are determined by identifying the nodes with the lowest energy consumption, intra-cluster distance, inter-cluster distance, and delay. The following outlines the multi-objective constraints that are considered for selecting the optimal CH:

- Energy Consumption: In the course of data exchange, nodes' energy is rapidly lost. Thus, the energy consumed by the transmitter during transmitting $n-bit$ data is E^{Tx} and the energy consumed by the receiver is E^{Rx}. The energy consumed by both transmitter and receiver during data transmission is given as follows:

$$E^{Tx}(n,d) = \begin{cases} n \cdot E^{RC} + n \cdot \in \cdot d^2 when d \le d_t \\ n \cdot E^{RC} + n \cdot E^p \cdot d^2 when d > d_t \end{cases} \tag{3}$$

$$E^{Rx} = n \cdot E^{RC} \tag{4}$$

where, E^{RC}represents the energy that is consumed while transmitting single bit of data, E^{p} indicates energy needed to process one piece of data, $\in$ signifies amount of consumed energy transmitting data in free space and d_t represents threshold distance.

Here, the threshold distance is represented as,

$$d_t = \sqrt{\frac{\in}{E^p}} \tag{5}$$

- ***Delay:*** The delay has a significant impact on data transmission. It is therefore expressed as,

$$\tau = \frac{max(\|D_q - E_j\| \cdot C_N}{C_N} \tag{6}$$

where, the total number of cluster nodes are represented as C_N.

- ***Distance:*** The distance between member nodes and its neighbors is calculated based on Euclidean distance between nodes D_q and E_j. The distance metric is calculated as,

$$D = \sum dis\ tan\ c\ e\left(D_q, E_j\right) \tag{7}$$

- ***Inter-cluster distance:*** The distance between each cluster center or cluster head node is referred to as the inter-cluster distance. It is calculated as,

$$\lambda = min\left\|\left(D_q - E_j\right)\right\|^2 \tag{8}$$

- ***Intra-cluster distance:*** The distance between member sensor nodes and the cluster center is known as the intra-cluster distance. The compactness of the network's different clusters is assessed using this metric. The intra-cluster distance is calculated as,

$$\psi = \frac{1}{N_S} \sum_{D=1}^{N_S} \sum_{E=1}^{N_C} \left\|D_q - E_j\right\|^2 \tag{9}$$

Thus, the node that fulfills the multi-objective constraints is considered as the best CH. Then, data is transferred through these selected CH.

Using hybrid OPOA, the fitness of every candidate solution is assessed using equation (10),

$$Fitness(F^*) = Min(E_C \cdot \tau \cdot D_{int\,er} \cdot D_{int\,ra}) \tag{10}$$

where, E_C denotes energy consumed by sensor nodes, τ represents delay during data transmission, inter-cluster and intra-cluster distance are represented as $D_{int\,er}$ and $D_{int\,ra}$.

In the above equation (10), the value of the multi-objective constraints should be low for choosing the best CH node. The fitness function integrates delay, distance, and energy consumption, each derived from established WSN radio models, to ensure that the theoretical equations directly correspond to practical sensor deployment conditions.

Step 3: Exploration phase of OOA for reducing energy consumption and delay

In OOA, the exploration phase involves various strategies, such as identifying the fish, attacking the fish, and updating the position.

According to the first strategy, a set of fish for each search agent is estimated using equation (11),

$$Fp_i = \{U_x | x \in \{1,2, \ldots\ldots, N_P\} \wedge F_x < F_i\} \cup \{U_{best}\} \tag{11}$$

where, Fp_i denotes a set of fish positions for i^{th} search agent, U_x represents position of x^{th} osprey and U_{best} indicates best solution.

Then, osprey selects a fish in a random manner from a set of fish Fp_i and move towards that position. Thus, the new shifted position of osprey is calculated as,

$$u_{i,j}^{P1} = u_{i,j} + k_{i,j} \cdot \left(f_{s_{i,j}} - R_{i,j} \cdot y_{i,j}\right) \tag{12}$$

Then, the new position is adjusted to ensure that the search agents stay within the boundaries of the search space. It is thus formulated as,

$$u_{i,j}^{P1} = \begin{cases} u_{i,j}^{P1}, if LB_j \leq u_{i,j}^{P1} \leq UB_j; \\ LB_j, if u_{i,j}^{P1} < LB_j; \\ UB_j, if u_{i,j}^{P1} > UB_j. \end{cases} \quad (13)$$

where, $u_{i,j}^{P1}$ represents new position of i^{th} osprey in j^{th} dimension according to phase 1 (i.e. exploration),$f_{s_{i,j}}$ signifies the fish that is selected for i^{th} osprey in dimension j, $k_{i,j}$ represents random number in the range [0, 1] and $R_{i,j}$ indicates a random number from set $\{1,2\}$.

Then, the location of the osprey is updated if the new position has an improved objective function value. Then, the position is updated using equation (14),

$$U_i = \begin{cases} U_i^{P1}, if F_i^{P1} < F_i; \\ U_i, else \end{cases} \quad (14)$$

where, U_i^{P1} indicates new position of i^{th} osprey due to exploration phase and F_i^{P1} denotes value of fitness function at new position.

Thus, the process of exploration helps the search agents escape local optima and move closer to the global optimum.

Step 4: PO algorithm's staying behavior for lowering inter- and intra-cluster distance

The Pyrrhura Molinae is a rare species that flies unexpectedly to any region of its proprietor's body and stays there for a while. This staying behavior can be represented as,

$$U_i^{t+1} = U_i^t + U_{best} \cdot Levy\big(dim()(0,1)(1, dim())\big) \quad (15)$$

where, the term $U_{best} \cdot Levy(dim())$ represents the bird's flight towards its owner and the factor $rand(0,1) \cdot ones(1, dim())$ signifies the birds random choice of a location on the owner's body to stay in which the term $ones(1, dim())$ signifies a vector in dimension dim.

In above equation (15), U_{best} provides the best solution with lowest multi-objective constraints for better CH selection.

Thus, the PO captures the random nature of the bird's movement, as well as its tendency to settle in one place after reaching its owner, blending both deterministic flight and random resting behavior.

Step 5: Termination

The suggested Hybrid OPOA algorithm stops its search when it reaches the maximum number of iterations, thereby returning the best optimal solution for selecting the optimal CH node.

The flow diagram representing the steps in Hybrid OPOA is illustrated below in Figure 3:

A. Computational Complexity of Hybrid OPOA

The computational complexity of Hybrid OPOA relies on the initialization and position updating processes, which are based on a combination of exploration and exploitation strategies. The computational complexity of initialization stage is $O(N_P \cdot h)$, where N_P denotes population size and h denotes number of problem variables. Then, computational complexity of position updating process based on exploration and exploitation behaviors is $O(2N_P \cdot dim \cdot h \cdot I)$ in which I signifies maximum iteration counts and the termdimsignifies dimension of optimization problem. Therefore, overall complexity of Hybrid OPOA is $O\big(N_P \cdot dim \cdot h(1 + 2I)\big)$. Thus, the newly introduced meta-heuristic hybrid OPOA successfully reduces the likelihood of becoming trapped in local optima and facilitates the identification of the optimal CH with reduced computational complexity.

The process of clustering helps secure and expedite data transmission in WSNs by reducing energy consumption and delay.

3.2. Hybrid Convolutional Auto-Encoder Dual-Key Transformer Network for Detecting Energy Utilization

First, real-time data on soil moisture, temperature, humidity, and water use is collected by WSN nodes. The member sensor nodes collect data, which is then sent to the CH node. After that, a CH node with the greatest fitness score sends the data to the base station [23, 24]. Thus, the DL structure for precision agriculture analyzes the farm data that is gathered. The amount of energy utilized and constraints that affect energy usage for precision agriculture are estimated by employing a DL based hybrid Convolutional Auto-Encoder Dual-Key Transformer Network (CAE-DktNet). The suggested hybrid CAE-DktNet model is developed by combining Convolutional Auto-Encoder (CAE) Network [25] with Dual-Key Transformer Network (DktNet) [26]. In this study, CAE-DktNet effectively estimates the amount of energy usage and factors that affect the energy utilization. The detection accuracy of CAE-DktNet is enhanced by employing a meta-heuristic optimization approach. In this concern, a novel Gooseneck Barnacle

Optimization (GBO) Algorithm [27] is used.

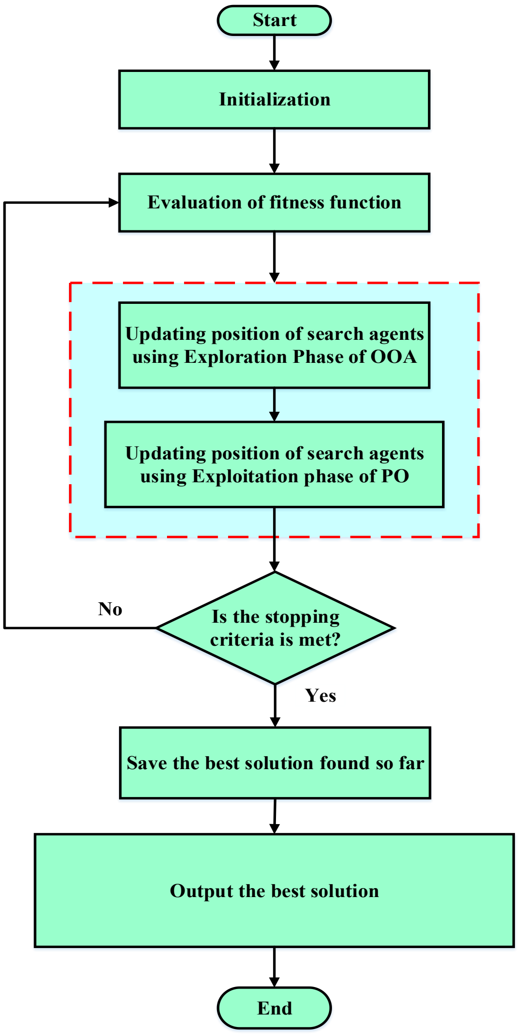

Fig.3. Hybrid OPOA workflow combining OOA exploration and PO exploitation for CH selection

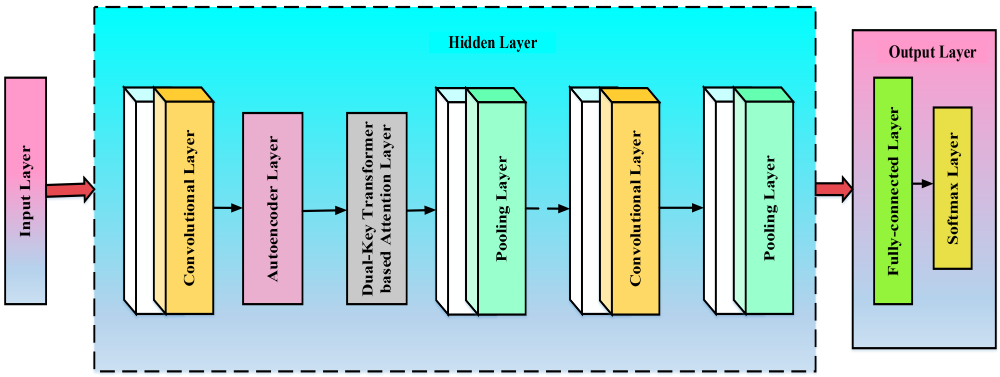

Fig.4. CAE-DktNet architecture framework

A CAE-Net coupled with a DktNet will provide an effective solution for identifying the energy used in precision agriculture. The CAE excels in automatically deriving spatial characteristics from agricultural sensor data, including temperature, humidity, and soil moisture, while simultaneously reducing the data's dimensionality. This is useful in modeling intricate trends without straining computing capability, and thus is best suited for real-time surveillance. Conversely, DktNet is dedicated to the temporal dependencies of sequential data, which enables it to monitor time-dependent changes in energy consumption, including variability due to weather conditions or equipment operation. Its dual-key attention mechanism ensures that the network can focus on both larger energy trends and local events, resulting in more accurate predictions. Combining CAE and DktNet can create a scalable and flexible system that maximizes energy efficiency by efficiently processing large-scale sensor data and enhancing decision-making in agricultural operations. The combination leads to a greater level of energy control, which ultimately promotes sustainability and affordability in accurate agricultural practices.

The created CAE-DktNet learner is trained to extract feature representations from raw sensor data, enabling it to classify the various states of energy utilization. The framework employs both unsupervised and supervised learning, utilizing an unsupervised autoencoder to initialize the convolutional layers. Figure 4 below is a schematic representation of CAE-DktNet:

The proposed CAE-DktNet comprises several convolutional layers, autoencoder blocks, pooling layers, a dual-key transformer-based attention module, and a fully connected layer followed by a Softmax layer. Hyperparameters and detection accuracy were validated using benchmark datasets and synthetic agricultural datasets simulating soil moisture, humidity, and irrigation conditions. This ensures that the model captures real-world agricultural variations, such as soil density, irrigation frequency, and diurnal weather cycles. The hyperparameter settings of the proposed DL framework are given below in Table 1:

Table 1. Hyper parameter setting of CAE-DktNet

Parameter	Value
Learning Rate	0.001
No. of Convolutional layers	3
Size of Kernel	3 × 3
No. of filters	128
Type of Pooling	Max-pooling
No. of transformer layers	4
No. of Attention Heads	6
Batch Size	64
Activation Function	ReLU
Dropout Rate	0.1
No. of epochs	100

Table 1 provided above outlines the hyperparameters for CAE-DktNet. These hyperparameter values may vary depending on the application.

At first, each input patch u derived from raw data collected from WSN is represented as $u \in \mathbb{R}^{k \times s \times s}$ in which $k$denotes various sensor readings and $s \times s$ denotes the size of data patch. Here, the raw sensor data are fed as input to the convolutional layers. The convolutional layers extract local features from the sensor data. The autoencoder block consists of both a standard autoencoder and a convolutional autoencoder. The standard autoencoder layer reconstructs input data to learn feature representations. The convolutional autoencoder layer applies depth-wise convolution to learn spatial features from sensor data by performing encoding and decoding operations. Thus, the output from these layers is expressed as,

$$O_{xj} = g(u_x) = \sigma(w_j \cdot u_x + b) \tag{16}$$

where, σ represents a non-linear activation function. Here, an activation function called "ReLu" is implemented.

$$\text{Thus, } \operatorname{Re}Lu(u) = \begin{cases} u & u \geq 0 \\ 0 & u < 0 \end{cases} \tag{17}$$

Then, the input u_x is reconstructed from output O_{xj} from the convolutional decoder for generating the estimate of input data. The estimate from input data is therefore expressed as,

$$\hat{u}_x = g'(O_{xj}) = \varphi(\widehat{w}_x \cdot O_{xj} + \hat{b}) \tag{18}$$

Thus, the estimate $\hat{u}_x$ is generated after each convolutional encoding and decoding.

The dual-key transformer-based attention network comprises three stages: estimation of dual keys, integration of dual keys, and computation of attention. Here, the attention layers are employed to learn the query, key, and value tensors. It is therefore expressed as,

$$(Q, K_1) = g_{chunk}\left(g_{Z_G^1}(W')\right) \tag{19}$$

$$(K_2, V) = g_{chunk}\left(g_{Z_G^2}(W')\right) \tag{20}$$

where, g_{chunk} represents the operation to compute the values of query, key and value tensors and $g_{Z_G^{(\cdot)}}(\cdot)$ denotes the fully-connected linear operation.

Then, the dual keys K_1 and K_2 are computed along the stream of query and value tensors. Thus, the integration of dual-keys will construct the dependence between Q and V. The final key values are then obtained by integrating the computed dual-key values. This is expressed as,

$$K^{dual} = K_1 + K_2 \tag{21}$$

Then, using the values of the query, dual keys, and value tensors, the channel-wise attention is calculated. The attention module suppresses the muddled channels and concentrates only on the crucial ones. Consequently, the channel-wise attention map is produced as,

$$g_{Attention}(Q, K^{dual}, V) = VSoft\,max\left(\frac{K^{dual}Q}{\upsilon}\right) \tag{22}$$

where, $Q, K^{dual}, V \in \mathbb{R}^{FZ\times E}$ are obtained by reshaping the tensors and υ denotes a scaling parameter that can be learned to alter the size of the dot product between the query and key tensors. Then, the multi-head dual attention is computed as,

$$\hat{A} = g_{Z_p}\left(g_{Attention}(Q, K^{dual}, V)\right) + A \tag{23}$$

where, A and $\widehat{A}$ represents the input and output feature maps from attention layer and $g_{Z_p}(\cdot)$ indicates the convolution operation.

The spatial dimensions and computational complexity of feature maps are then reduced by the pooling layers. In this case, max-pooling is considered to minimize the dimensionality of the data by selecting the maximum value within each pooling region. Thus, the operation of pooling simplifies feature maps, thereby retaining important information. The output from the max-pooling layer is modeled as,

$$O_{xj} = max\left(u_{xj}\right) \tag{24}$$

Finally, the fully connected layer of CAE-DktNet aggregates useful and important features for classification. After a fully connected layer, a Softmax layer classifies energy utilization states into low, medium, and high categories based on the extracted features. Therefore, the output from the softmax layer is modeled as,

$$\hat{y}_x = \frac{e^{O_X}}{\sum_{l=1}^{2} e^{O_X}}, x = 0,1 \tag{25}$$

The CAE-DktNet model's loss function in this instance is cross-entropy, which is decreased to improve detection and classification accuracy. To reduce the cross-entropy loss, the weight and bias parameters of the neural network are adjusted. This is how the loss function is expressed:

$$£(w,b) = -\left[y\ \log(\hat{y}_0) + (1-y)\log(\hat{y}_1)\right] \tag{26}$$

where, w, b represents the weight and bias parameters of CAE-DktNet, y indicates the actual data and $\hat{y}$ denotes the predicted data.

The weight and bias parameters from the above equation (26) are fine-tuned to achieve improved detection and classification accuracy. This is accomplished by utilizing a new GBO algorithm.

A. Optimizing hyperparameters of CAE-DktNet using GBO

The distinctive feeding and attachment patterns of gooseneck barnacles served as inspiration for the proposed GBO algorithm, a revolutionary meta-heuristic optimization technique. By carefully positioning themselves on rocks to absorb plankton carried by ocean currents, these barnacles maximize food capture while consuming the least amount of energy. By discovering the best answers in intricate search spaces and striking a balance between exploration and exploitation to enhance performance in various optimization tasks, the algorithm mimics this behavior, much like barnacles adjust to their changing surroundings. The following describes the actions taken in GBO to increase the detection accuracy:

Step 1: Initialization

Initialization involves setting up parameters such as the issue dimension, maximum number of iterations, and population size. The search field is then filled with a random pool of potential answers. The process of initialization is thus modeled as in equation (27),

$$V = \begin{bmatrix} (v+k)_{1,1}(v+k)_{1,2} \cdots (v+k)_{1,h} \\ \vdots\vdots\vdots \\ \vdots\vdots\vdots \\ (v+k)_{N,1}(v+k)_{N,2} \ldots (v+k)_{N,h} \end{bmatrix} \tag{27}$$

where, k denotes the length of gooseneck, the parameters N and h represents the population size and number of decision variables to be optimized.

Step 2: Calculation of fitness function

In this step, the fitness of each candidate in the search space is evaluated to find the best candidate solution. Here, the value of the fitness function depends on two important constraints, like maximum accuracy and minimum error rate. Thus, the value of the objective function is computed using equation (28),

$$\text{Fitness} = \text{Max}(\eta) \cdot Min(\varepsilon) \tag{28}$$

where, η denotes the detection accuracy and ε indicates the error.

In the above equation (28), the parameter η should be maximized and $\mathcal{E}$ should be minimized to obtain the best performance.

Step 3: Updating position based on the Exploration phase

The exploration phase of GBO mimics how gooseneck barnacles initially search for the best spot on rocks. The algorithm explores the search space widely, trying out different positions to find potentially optimal solutions. This helps in covering a broad area to avoid getting stuck in local optima. In GBO, sperm for mating will be present in a designated area of the water. The gooseneck barnacles locate the best spot with sperm by using their penis to navigate the search space. Generally, a significant wave height of 0.8 to 3 meters is considered considerable for goosenecks. Thus, the significant height of the wave is calculated using equation (29),

$$WH_S = 4\sqrt{WH^{2M}} \tag{29}$$

The above equation is rewritten as,

$$WH_S = 1.5 - \left(\frac{I(1.5-0.2)}{I_{max}}()\right) \tag{30}$$

where, I denotes the iteration count and I_{max} signifies maximum number of iterations.

To determine the ideal area for mating, the wave height will decrease with each iteration, and the range of wave intensities will be investigated. Here, a neighboring spiral region for sperm casting is modeled as,

$$S\left((V+k)_r, \left(S_{pW}\right)_q\right) = D_r \cdot e^{cI_{max}\cos\left(2\pi I_{max}()\left(S_{pW}\right)_q\right)} \tag{31}$$

where, $(V+k)_r$ indicate the r^{th} gooseneck barnacle, D_r denotes the distance of the r^{th} gooseneck for q^{th} sperm region for performing mating process, c represents the constant for defining the spiral shape and t signifies a random number in the interval [-1, 1].

Here, the distance is calculated as,

$$D_r = (V+k)_r - \left(S_{pW}\right)_q \tag{32}$$

where, $\left(S_{pW}\right)_q$ denotes the q^{th} sperm region.

Step 4: Updating position based on the Exploitation phase

Once potential good spots are found, the algorithm focuses on fine-tuning and exploiting these areas to find the best solution. It refines its search around these positions, similar to barnacles adjusting their placement for optimal food capture.

Here, the position of new search agents is updated, and their migration towards newly generated offspring is simulated using a movement vector. The movement vector is expressed as,

$$\Delta(V+1)_{r+1} = w_{d_r} + MS(V+1)_{r_{dim}} \tag{33}$$

$$(V+1)_{r+1} = (V+1)_r + \Delta(V+1)_{r+1} \tag{34}$$

Based on wind direction nd notable wave activity, the goosenecks adjust their locations toward the target zone using the aforementioned equation (34).

Sometimes, only one sperm location is left because of the blowing of the wind and the intensity of the waves. The following equation (35) is used in this case to update the positions of the search agents.

$$(V+1)_{r+1} = (V+1)_r + Levy * (V+1)_r \tag{35}$$

where, inside the range [0 359], w_{d_r} indicates the wind direction that is derived throughout the search space radius and M_{dim}represents the dimension of target towards best solution.

In the above equation (35), the Levy flight is determined as,

$$Levy(X) = 0.01 \times \frac{z_1 \times \sigma}{|z_2|^{\frac{1}{\alpha}}} \tag{36}$$

where, z_1,$z_2$signifies random numbers in the range [0 to 1] and α represents a constant that is set to 1.5.

Finally, the best global solution with the highest fitness value is estimated, along with the best location and target.

Step 5: Termination

The algorithm stops searching for solutions once it has converged to an optimal or satisfactory solution. In addition to theoretical optimization, GBO was validated under simulated farm conditions with fluctuating connectivity and heterogeneous workloads, ensuring stable convergence and practical feasibility.

Computational complexity of GBO

The procedures of startup, fitness function evaluation, and offspring generation all affect the computational complexity of GBO. The computational complexity of initialization process is $O(N \times h)$. The computational complexity during calculation of fitness function is $O(I(N\, log\, N)_{max}())$. Finally, the computational complexity in generating new offspring is $O(I(N \times h)_{max}())$. Thus, the overall computational complexity of GBO is represented as,

$$O(GBO) = O\left(Nh + I\, log\, N_{max_{max}}\right) \tag{37}$$

where, N denotes the size of population, h represents dimension of the problem and I_{max} signifies iteration counts.

Two decision variables, a population size of 100, and a maximum of 1000 iterations are all configured in GBO. Precision agriculture can enhance crop output by employing an integrated strategy, which enables more precise detection and classification of energy consumption. And, the developed DL framework efficiently learns robust feature representations from WSN data.

4. Results and Discussion

Network Simulator Version 3 (NS-3) is used to simulate the results of the proposed research study on an Intel Core 5 personal computer equipped with 64 GB of hard drive space and 1 GB of RAM. The parameter setting of WSN is described below in Table 2:

Table 2. Parameter setting of WSN

Parameter	Value
Node Density	250
Transmission Range	300 meters
Data Rate	250 kbps
Packet Size	100 bytes
Delay	50ms

4.1. Performance Evaluation

The suggested model is assessed using performance metrics. The obtained metric values are compared with some existing DL models and multi-objective optimization approaches like O-CNN [16], DQN [17], O-RNN [18], ANN [19], DCNN [20], EDGENN [21], DRL [22], BMAFMO [28], MSFOA [29], BCMO-BCO [30], and AVO [31] to evaluate the efficiency of the presented model. The metrics considered for evaluation are calculated using the equations below:

Network Lifetime: The ratio of the whole time the network takes to perform its intended task to the total time it takes to simulate the network is known as the network lifespan. The calculation is done with equation (38).

$$NL = \frac{Totaltimetakenbythenetwork}{Totalsimulationtime} \tag{38}$$

Packet Delivery Ratio: The PDR is the ratio of correctly received packets to the total number of packets delivered. PDR is therefore calculated using equation (39),

$$PDR = \frac{Numberofpacketsreceivedsuccessfully}{Totalamountofpacketstranmsitted} \tag{39}$$

Energy Consumption: The network's overall energy consumption, which includes the energy required by every sensor node to send data packets, is referred to as the energy consumption measure. Thus, the formula in equation (40) is used to calculate energy usage.

$$E_C = \frac{Energyutilizedbyeachsensornode}{Totalenergyconsumedbythenetwork} \tag{40}$$

Throughput: The rate of data flow throughout a whole network is known as throughput. Equation (41), which is used for the computation,

$$Thr = \frac{AveragePacketSize \times Numberofsuccessfullyreceivedpackets}{Totaltimefordeliveringparticularamountofdatapackets} \tag{41}$$

The graphs obtained through simulation are illustrated in the following figures:

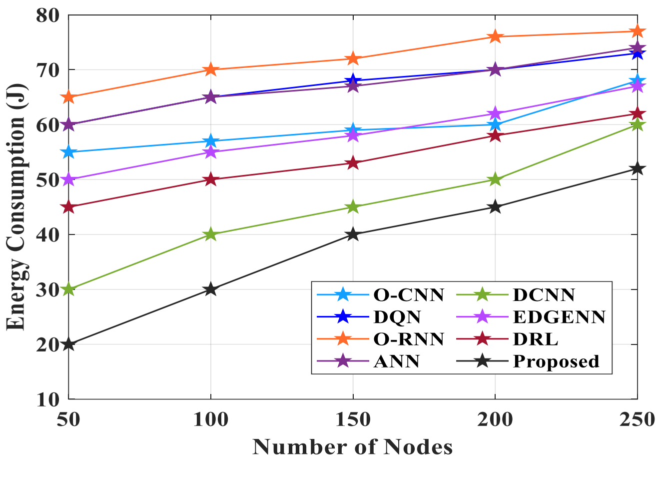

Fig.5. Comparison of energy consumption under varying sensor nodes

Figure 5 illustrates the amount of energy each approach consumes as the number of nodes increases from 50 to 250. The proposed method consistently consumes the least energy, starting at around 22 J for 50 nodes and reaching approximately 39 J for 250 nodes. The O-RNN method consumes approximately 33 J to 54 J of energy. In contrast, DCNN, DRL, and EDGENN exhibit higher energy consumption, peaking at around 75 J. ANN and DQN have moderate consumption, ranging from 45 J to 65 J.

As the node count of a WSN rises from 50 to 250, Figure 6 displays the throughput for various techniques. The proposed method achieves the highest throughput, starting at approximately 94 kbps with 50 nodes and decreasing to around 68 kbps at 250 nodes. O-CNN and DCNN start at 82 kbps and drop to around 60 kbps. O-RNN, EDGENN, and DRL exhibit a similar trend, decreasing from approximately 74 kbps to 52 kbps. ANN and DQN perform the worst, dropping from 70 kbps to 45 kbps.

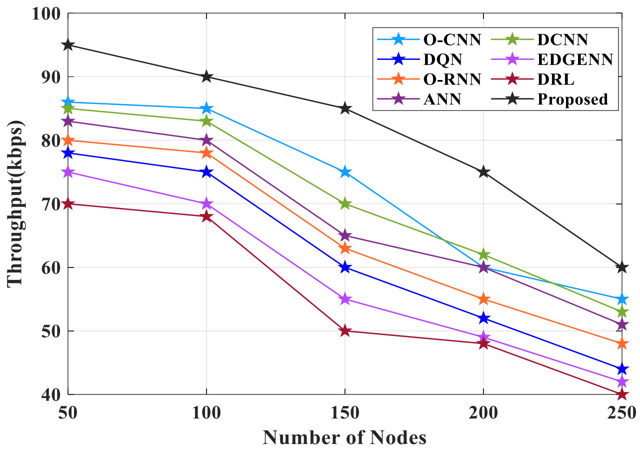

Fig.6. Comparison of throughput under varying sensor nodes

Figure 7 above shows the PDR in percentage against the number of nodes for different models. The proposed model achieves the highest PDR, reaching 98% at 250 nodes. Other models, such as EDGENN and DRL, demonstrate good performance with PDRs of around 90% and 85%, respectively, at 250 nodes. Models like DCNN and O-RNN have lower PDRs, at around 55% and 60%, respectively. This indicates that the proposed model maintains superior packet delivery performance as the network size increases.

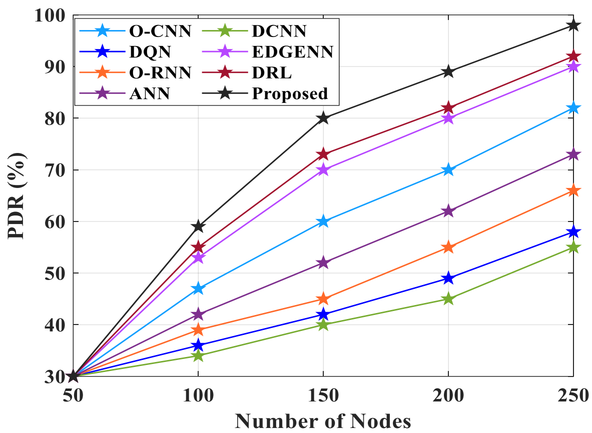

Fig.7. Comparison of PDR under varying sensor nodes

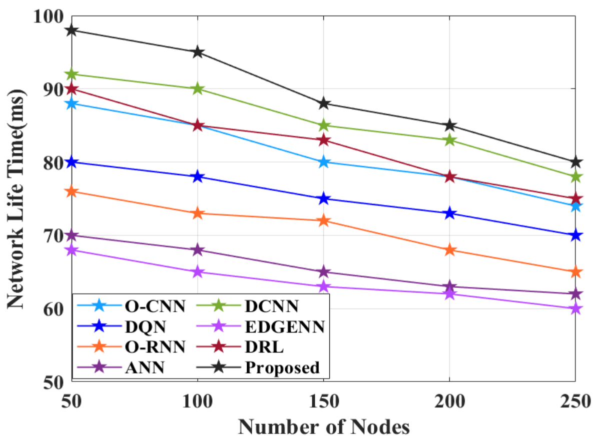

Fig.8. Comparison of network lifetime under varying nodes

The figure 8 depicts the network lifetime (in milliseconds) under varying node numbers for different models. The proposed model consistently maintains the highest network lifetime, starting near 100ms at 50 rounds and decreasing to around 85ms at 250 rounds. Other models, such as DCNN and EDGENN, follow, with lifetimes dropping from approximately 85ms to 75ms and 75ms to 65ms, respectively. ANN has the lowest lifetime, decreasing from around 70ms to below 60ms. This shows the proposed model's superior energy efficiency.

The delay of several models as the number of nodes rises is contrasted in Figure 9 above. The models include O-CNN, DCNN, DQN, EDGEANN, O-RNN, DRL, ANN, and a proposed model. The proposed model consistently achieves the lowest delay across all node counts, indicating better performance compared to the other models as the network size grows.

Figure 10 illustrates the accuracy of various methods as the node count of a WSN increases from 50 to 250. The suggested approach achieves the highest accuracy, reaching approximately 97% at 250 nodes, after starting at around 88% with 50 nodes. The O-CNN and DQN methods demonstrate moderate accuracy, ranging from 70% to 82%. O-RNN, DCNN, and EDGENN have lower accuracy, ranging from 50% to 72%. ANN and DRL perform the worst, with accuracy ranging from 47% to 64%.

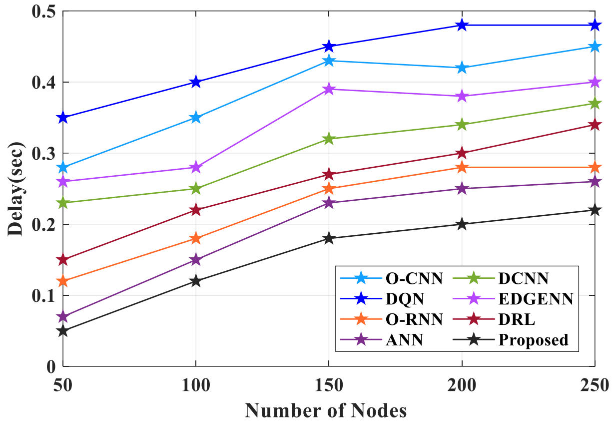

Fig.9. Comparison of throughput under varying sensor nodes

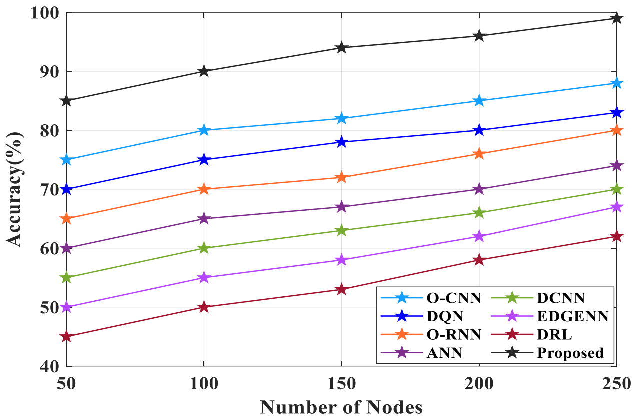

Fig.10. Comparison of accuracy under varying sensor nodes

Table 3. Estimation of performance under various rounds

Number of Rounds	Network Lifetime (ms)	Packet Delivery Ratio (%)	Throughput (kbps)	Energy Consumption (Joules)	Delay (ms)
200	98	99.5	95	23	0.06
400	95	98.9	88	29	0.13
600	87	99.1	80	34	0.17
800	85	99.2	78	45	0.23
1000	80	99.3	67	54	0.27

Table 3 above displays the estimation of several performance measures in a WSN under different sensor nodes. As the number of nodes increases, the table shows that all metric values, except for the latency metric, decrease. This demonstrates the improved effectiveness of the suggested model.

The above tables (4 and 5) demonstrate the energy utilization and residual energy available for precision agriculture. From the tables, it is observed that the proposed approach utilizes less energy while maintaining a high residual energy, which helps achieve better crop yields in precision agriculture.

Thus, the simulation parameters from tables and graphs demonstrate the improved efficiency of the proposed model in detecting energy utilization for precision agriculture.

Table 4. Comparison of energy utilization and residual energy from various methods

Methods	Utilization of Energy (mW)	Residual-Energy Leftover (mW)
DQN [17]	65.7	44.6
RNN [18]	69.4	40.2
DCNN [20]	78.2	53.5
DRL [22]	56.7	34.5
Proposed	35.4	75.2

Table 5. Comparison of energy utilization and residual energy from various multi-objective optimization approaches

Methods	Utilization of Energy (mW)	Residual-Energy Leftover (mW)
BMAFMO [28]	65.7	44.6
MSFOA [29]	78.2	53.5
BCMO-BCO [30]	56.7	34.5
AVO [31]	80.4	47.2
Proposed	35.4	75.2

4.2. Ablation Study

By methodically eliminating one module at a time and assessing the results, an ablation study was conducted to confirm the necessity of each element in the proposed framework. OPOA for CH selection, CAE-DktNet for energy utilization detection, and GBO for hyperparameter optimization are the three main elements being examined. Table 6 summarizes the findings.

Table 6. Ablation study of the proposed approach

Variant	Accuracy (%)	Throughput (kbps)	PDR (%)	Energy Consumption (J)	Delay (s)	Network Lifetime (ms)
Full Model (OPOA + CAE-DktNet + GBO)	99.2	68	98	39	0.23	85
Without OPOA	96.7	61	94	52	0.35	63
Without CAE-DktNet	95.8	59	92	55	0.41	58
Without GBO	97.2	63	95	47	0.29	71

The ablation results in Table 6 highlight the contribution of each component to the overall framework. In the absence of OPOA, CH selection is suboptimal, resulting in increased energy consumption and a shorter network lifetime. Excluding CAE-DktNet reduces detection accuracy and weakens the ability to identify constraints affecting energy usage. Removing GBO results in less effective hyperparameter tuning, which lowers model accuracy and increases resource overhead. All three elements operate optimally when combined, demonstrating how well they complement one another and enhance the suggested framework's resilience and efficiency.

4.3. Statistical Analysis

Every experiment was conducted 20 times with different random seed values and diverse WSN deployment conditions to confirm the resilience of the suggested methodology. 95% confidence intervals (CIs) were computed to ensure statistical reliability, and the results are presented as the mean ± standard deviation (SD). Results were found to be statistically significant ($p < 0.05$) when paired t-tests were used to compare the suggested strategy with baseline procedures. The low SD values across multiple trials confirm the stability and reproducibility of the proposed framework.

Table 7. Statistical analysis with mean, SD, CI, significance

Metric	Proposed Framework (Mean ± SD)	95% CI	Baseline Avg.	p-value
Accuracy (%)	99.2 ± 0.3	[98.6 – 99.7]	96.8	< 0.01
Throughput (kbps)	68.0 ± 1.1	[66.2 – 69.5]	61.5	< 0.01
PDR (%)	98.0 ± 0.4	[97.3 – 98.7]	94.2	< 0.01
Energy Consumption (J)	39.0 ± 0.8	[37.5 – 40.3]	45.6	< 0.01
Delay (s)	0.23 ± 0.02	[0.19 – 0.27]	0.36	< 0.05
Network Lifetime (ms)	85.0 ± 1.5	[82.2 – 87.6]	72.4	< 0.01

The statistical analysis in Table 7 confirms the reliability of the proposed framework. Across 20 independent runs, the standard deviations remain consistently low, indicating stable performance. The 95% confidence intervals are narrow, further reinforcing the robustness of the results. Moreover, paired t-test analysis shows that the improvements achieved by the proposed method over baseline approaches are statistically significant ($p < 0.05$). These findings validate that the observed performance gains are not coincidental but a result of the effective integration of OPOA, CAE-DktNet, and GBO within the energy utilization detection framework.

4.4. Discussion

The reported high performance of the proposed OPOA + CAE-DktNet + GBO framework, with 99.2% accuracy and a delay of 0.23 s, was achieved under the controlled NS-3 simulation environment defined in Table 2. These results represent idealized conditions with fixed parameters and minimal interference, highlighting the potential of the framework. However, real-world deployments may introduce uncertainties such as hardware variability, interference, and unpredictable network dynamics. Future work will therefore focus on validating the framework through real-world testbed implementations in agricultural settings to assess robustness under practical conditions. Comparative evaluation against existing DL and multi-objective optimization models, including O-CNN [16], DQN [17], O-RNN [18], ANN [19], DCNN [20], EDGENN [21], DRL [22], BMAFMO [28], MSFOA [29], BCMO-BCO [30], and AVO [31] under the same NS-3 simulation setup demonstrates that the proposed approach consistently outperforms baselines in performance metrics. The ablation study further highlights the complementary contributions of individual components: GBO provides effective hyperparameter tuning, achieving higher stability and lower delay than PSO and GA; CAE-DktNet surpasses GRU, LSTM, and CAE in detection accuracy; and OPOA allows optimal CH selection for lower energy consumption and longer lifetime. Together, these integrated strategies establish a robust solution for energy-efficient and reliable data management in precision agriculture WSNs.

5. Conclusions

This research proposes a DL-based framework for detecting energy use in precision agriculture utilizing WSNs. The goal is to maximize energy use while maintaining the quality of the data. The system can process sensor data intelligently and prioritize using DL models to identify patterns such as moisture levels, temperature changes, and crop health. It only sends important information, not all of it, which decreases the amount of data transmitted and, as a result, the power consumed during transmission. This method also prolongs the lifespan of a network and provides reliability through ongoing monitoring. Additionally, DL can identify the optimal sensor activation times, thereby reducing energy waste. In this context, a new multi-objective clustering-based energy utilization detection model is developed for precision agriculture. First, the hybridized variant of the optimization process introduced will identify the best CH to transmit the data by combining with OOA and PO. The hybrid DL model is then constructed to predict energy utilization and classify the various states of energy utilization with the assistance of the developed CAE-DktNet. In this way, the sustainability and efficiency of WSNs are enhanced in farming settings, which improves the overall management of crops. The performance of the given strategy is measured in terms of several key performance metrics, including energy use, throughput, network lifetime, packet delivery percentage, delay, and accuracy. The results of experiments indicate the effectiveness of the offered approach at various sensor nodes and rounds.

Future Work: In the future, the efficiency of the deep classifier model is enhanced by employing a novel hybrid optimization algorithm. Also, a robust adaptive learning approach is employed to optimize sensor activation schedules, focusing energy use on periods of significant agricultural changes. This strategy would increase the lifespan of WSNs, guarantee ongoing monitoring, and reduce the need for field maintenance or battery changes.

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