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RESEARCH ARTICLE

A self-driven dual reinforcement model with meta heuristic framework to conquer the iot based clustering to enhance agriculture production

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Abstract

In agriculture, irrigation is essential for providing water to crops based on the type of soil they are grown in. To achieve success in farming, it is important to evaluate soil fertility, temperature, rainfall and set irrigation schedules. In this work, to enhance agricultural production, an IoT-based hydration system that utilizes soil moisture and humidity sensors to keep an eye on soil conditions and water crops precisely is developed. This system effectively manages water usage in farming, resulting in an efficient conservation of water resources. The proposed model is categorized into four main phases: (a) Pre-processing; (b) Clustering; (c) Feature extraction; (d) Classification. Initially, the collected raw data is pre-processed *via* a data-cleaning approach. From the pre-processed data, DB scan is used to cluster the data. From the clustered data, the important feature is extracted by using statistical features like mean, standard deviation, kurtosis, and skewness. Subsequently, from the extracted features, the most optimal features are selected *via* a new hybrid meta-heuristic optimization model referred to as Cuckoo search-based Levy adolescent identity search algorithm (CLAIS). The projected CLAIS model is the conceptual amalgamation of the standard Cuckoo search optimization (CSO) and adolescent identity search algorithm (AISA), respectively. CLAIS-based deep Q network (CLAIS-DQN) classifier is used to classify the optimal features. DQN is an efficient solution to offload the request optimally which improves the overall performance of the network. The proposed model is implemented using the PYTHON platform. The proposed model has recorded the highest detection accuracy as 96%.

Keywords: Reinforcement model, IoT, Agriculture production, Adolescent identity search algorithm, DQN.

Introduction

Improved and sustainable farming practices are needed to address unfavorable climatic circumstances due to the increased worldwide need for food and fiber. Incorporating such sustainable practices would be better to using conventional methods for increasing the production of agricultural products from the available arable land in the face of declining soil and water quality (Singh, A. *et al*., 2020) (Gil, J.D.B., *et al*., (2020). Sustainable increases in agricultural productivity are critical to addressing multiple sustainable development goals (SDGs), including zero hunger (SDG 2), no poverty (SDG 1), and good health and well-being (SDG 3) (Lu, Y. & Young, S., 2020) The increasing demand of food due to ever-growing population have resulted in intensive agricultural practices including unprecedented use of agro-chemicals, livestock generation (for meat and other sources of income), exploitation of water resources etc. This has further aggravated the situation by release of GHG (due to agricultural activities) and resulting in pollution of natural resources. An extremely high rate of land degradation brought on by climate change is producing more desertification and nutrient-deficient soils (Arora, N.K., (2019) (Bartzas, G. & Komnitsas K., 2020). Assessment of agricultural production sustainability is a multi-dimensional task that involves the quantification of various economic, social and environmental indicators at different scales and uncertainty levels (Zhang, X., *et al*., 2020) (Ruan, J., *et al*., 2019). Since agriculture have been

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facing lot of difficulties, new technologies can provide suitable solutions. Smart farming use technologies such as robotics, drones and AI, increasing the quantity and quality of products while minimizing the need for human labor. The Internet of Things (IoT) is one promising technique to achieve precision agriculture, which is expected to greatly increase yields. IoT systems can help farmers with various sensors and actuators so that farmers can know in real time the growth status and environment in their farms, and make timely actions to keep the optimal growth status (Singh, R.P *et al*., 2021) (Liu, S., *et al*., 2019).

However, integrating IoT devices in agriculture comes at a significant expense. Currently, the majority of IoT devices are used in agriculture in controlled environments like greenhouses and cattle farms. Open-field agriculture, which holds the solution to the world's food shortage, is still not receiving a widespread promotion (Bu, F. & Wang, X., 2019) (Haseeb, K., *et al.* 2020).

Products made from nanotechnology that are used in agriculture are essential for improving plant development and crop productivity. They are a more preferable option for farmers than traditional chemicals and methods because to a number of characteristics, including their small size, portability, ease of handling, long-term storage and high effectiveness. Since nanoparticles are toxic in nature, since the crystal structure of nanoparticles also influences nano-toxicity, nanoparticles, when dissolved, release soluble ions and cause an inhibitory effect on seed germination (Chen, J. & Yang, A., 2019).

Modern agricultural IoT monitoring systems include an open agricultural IoT service platform as its foundation. This platform establishes a mqtt message service platform as well as data storage, big data analysis, and processing capabilities. The support layer of the IoT's hierarchical structure is where the IoT platform is located. Users can build low-cost, secure, reliable, and agricultural IoT applications with large data analytic capabilities using this platform. The open IoT platform requires significant computing resources to carry out these tasks, hence cloud computing technology was chosen to build the IoT service platform. For effectiveness and reliability in large-scale productions, more simulation tests have to be conducted (Al-Qurabat, A.K.M., *et al* 2021). In a smart agriculture IoT system based on edge-cloud computing with deep reinforcement learning models, sensors were employed to collect the environmental parameters, such as air temperature and humidity, which are analyzed by mining algorithms. Deep reinforcement learning makes proper adjustments in environmental parameters to be deployed for crop growth (Wang, P., *et al* 2021), (Xue, D. & Huang, W., 2020).

In the proposed method IoT sensors are used to gather the environmental data such as temperature, humidity of the air and soil. A hybrid meta-heuristic aware reinforcement learning is incorporated with a hybrid meta-heuristic-based duel DQN model for achieving a better agriculture-supportive model. Dueling DQN structure added to the network head allows the network to better differentiate actions from one another, and significantly improves the learning. The data collected by IoT are analyzed based on day, month, and year to identify the climate that has the highest level of production. In addition, the water level in the soil can also be monitored and provide sufficient level for proper crop growth.

This study's major contribution is exemplified below:

- To cluster the significant data, DB Scan is used.
- To select the optimal features, a new hybrid meta-heuristic optimization model Cuckoo search based Levy adolescent identity search algorithm (CLAIS) is used.
- To classify the most optimal features, a hybrid meta-heuristic-based duel DQN model (CLAIS-DQN) is incorporated. The CLAIS-DQN algorithm helps to onquer the clustering issues by executing Sa self-driven clustering process.

Literature Review

"*Some of the recent research works related to enhancing agricultural production were reviewed in this section*".

In 2019, Rajput and Kumaravelu (Rajput, A. & Kumaravelu, V.B., 2019) attempted to design a cost-effective clustering algorithm to obtain energy-efficient sustainable WSN while maximizing node density and coverage area. By utilizing the fuzzy c-means (FCM) clustering technique to reduce the data transmission distance between sensor nodes, the proposed approach's first goal is to Smaximize energy efficiency. The second goal is to choose an appropriate cluster head node (CHN) based on the assessed likelihood of achieving network scalability.

In 2022, Yang *et al.,* proposed a S (R-SAC) algorithm for agricultural scenarios to realize safe obstacle avoidance and intelligent path planning of robots. This work offers an offline expert experience pre-training technique, which increases the training effectiveness of reinforcement learning, in order to address the time-consuming problem of Sthe exploration process of reinforcement learning.

In 2020, Liu and Zhang have introduced a double elite co-evolutionary genetic algorithm (DECGA) and deep reinforcement learning (dueling DQN) to estimate the parameters of variogram single or nested models so as to achieve better generalization performance. The DECGA can get the global optimal solution faster than GA with the help of dueling DQN, which can set the hyper-parameters according to the state of DECGA.

In 2021, Anand *et al.* have proposed a deep learning framework, AgriSegNet for automatic detection of farmland anomalies using multiscale attention semantic segmentation of UAV acquired images. This model is useful for monitoring of farmland and crops to increase the efficiency of precision farming technique.

In 2023, Balaji V, Purnendu B, Acharjee, Muniyandy Elangovan, Gauri Kalnoor, Ravi Rastogi, Vishnu Patidar have proposed developing a semantic framework for categorizing IoT agriculture sensor data, a machine learning and web semantics approach.

In 2020, Budhiraja *et al.* proposed a deep reinforcement learning (DRL)-based control scheme in the underlay S (D2D) communication. D2D communication increases spectral efficiency by reusing spectrum resources using cellular user equipment (CUE). The combined resource block (RB) scheduling and power control approach to increase the network's total rate while taking user fairness across all links into account.

In 2019, Huang *et al*. proposed an improved deep Q-network (DQN) method for PolSAR image classification, which can generate amounts of valid data by interacting with the agent using the ϵ-greedy strategy. The PolSAR data are pre-processed to reduce the influence of speckle noise and extract the multi-dimensional features, which I then, along with the corresponding training image are then fed into a deep reinforcement learning model tailored for PolSAR image classification.

In 2020, Oh and Han proposed a mechanism that could enable autonomous drone path finding over a large target area without size limitations, one of the challenges of ML-based autonomous flight or driving in the real world. One of the problems with ML-based autonomous flight or driving in the real world is size limitations. The suggested mechanism could enable autonomous drone path finding across a vast target region without these restrictions.

In 2021, Jembre *et al.* configured the quadrotor to fly autonomously by using agents (the machine learning schemes being used to fly the quadrotor autonomously) to learn about the virtual physical environment. From an initial point, the quadrotor flies to the target position. The quadrotor is rewarded when the agent moves it toward the intended location; otherwise, it is penalized.

In 2021, Liu *et al.* proposed an efficient on-ramp merging strategy (ORMS) to coordinate vehicle merging in multi-lane traffic. The coordination of vehicle merging in multi-lane traffic is advocated using the effective ORMS. They have created a model of the lane-to-lane traffic flow irregularities. A reinforcement learning-based lane selection model has been developed for the coordination of cars in multi-lane traffic.

In 2021, Zhang *et al*., developed a multi-objective decision-making system (MDMS) that could simultaneously handle multiple problems and objectives in a small watershed based on the relationships among land, water and economy. The watershed operational process was thoroughly simulated using the MDMS in conjunction with the watershed hydrological model and economic benefit evaluation model.

Problem Statement

IoT-based clustering for enhancing agriculture production is a promising technology, but it also has some limitations. One of the main limitations is the high cost of implementation and maintenance. IoT devices, sensors, and other hardware components required for the system can be expensive, especially for small-scale farmers. Additionally, the system requires a reliable power source, internet connectivity, and specialized personnel to maintain and operate it, which can be challenging to provide in rural areas. Another limitation is the lack of standardization in IoT devices and protocols, which can make it difficult to integrate different systems and ensure compatibility between different devices. Privacy and security concerns are also major limitation of IoT-based clustering in agriculture. The sensitive data collected by the IoT devices must be protected from unauthorized access and hacking. This requires a robust security system and regular updates to prevent potential security breaches.

Proposed Methodology

IoT based clustering is a technology that uses IoT devices, sensors, and other hardware components to gather data from agriculture fields and use clustering algorithms to analyze this data to enhance agriculture production. The goal of this technology is to provide farmers with valuable insights into the health and growth of their crops, soil quality, weather conditions, and other factors that impact agriculture production. To conquer different farming issues that occur in the agriculture, this research work developed a novel IoT-based clustering to enhance agricultural production. The proposed model is composed of three key phases: (a) Pre-processing, (b) Feature extraction, and (c) Classification. Let the collected raw data be denoted as $D_a^{inp}; a = 1,2, \ldots c$. Here, c denotes the count of data samples. Figure 1 explains the overall architecture of the proposed model and includes three major phases.

Step 1: Pre-Processing

Initial pre-processing involves a data-cleaning approach on the constructed core data D_a^{inp} . The pre-processed data acquired after pre-processing is denoted as D_a^{pre}.

Step 2: Clustering

Subsequently from the pre-processed data, the features are clustered by using DB Scan.

Step 3: Feature Extraction

From the clustered data, the significant feature is extracted by utilizing features like mean, standard deviation, kurtosis, and skewness. These extracted features are referred as F.

Step 4: Classification

Using the selected optimal features $F(opt)$, the most optimal features are selected via a new hybrid meta-heuristic optimization model referred as Cuckoo search based levy adolescent identity search algorithm (CLAIS). To enhance the prediction accuracy of the projected model, a meta-heuristic-based duel DQN classifier makes the IoT-based clustering to enhance agricultural production. The final outcome from the classifier is the predicted outcome. In this approach, the true positive rate (TPR), true negative rate (TNR), false positive rate (FPR), and false negative rate (FPR) are considered for fetching most effective classification. Figure 1 shows the overall proposed architecture.

Pre-Processing

In this research work, the pre-processing is done by data cleaning approach.

Data cleaning

Initially, the collected raw data D_a^{inp} is pre-processed *via* data cleaning. Data cleaning, also known as data cleansing or data scrubbing, is the process of identifying and correcting inaccuracies, inconsistencies, and missing values in a dataset. The goal of data cleaning is to improve the quality and reliability of the data so that it can be used effectively for analysis, modeling, and decision-making. Data cleaning is a necessary step in the data analysis process as it can significantly impact the accuracy and validity of the results obtained from the data. Common techniques used in data cleaning include removing duplicates, handling missing values, detecting and handling outliers, formatting and transforming data, data normalization, and data reduction. The specific techniques used depend on the nature of the data and the goals of the analysis. A clean dataset is essential for obtaining accurate and meaningful results from the data analysis process. The cleaned data is passed to the clustering phase.

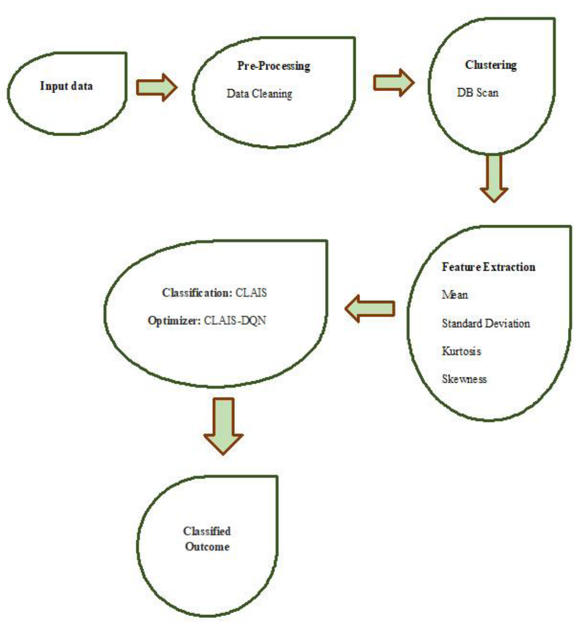

Figure 1: Overall architecture diagram

Clustering

In this research work, the clustering process is done using DBSCAN. Clustering is a data mining technique that can be used to enhance agriculture production by grouping similar data points into clusters. The proposed IoT-based solution for agriculture uses soil sensors, environmental sensor-actuator nodes, and rain-gauge sensors. The data collected from these sensors includes district, year, month, rainfall, average rainfall, temperature, average temperature, pressure, and average pressure. These data are analyzed and clustered using a hybrid meta-heuristic-based reinforcement learning approach to create a more effective agriculture support model.

DBSCAN

The pre-processed data is passed as an input to the clustering phase. Density-based spatial clustering of applications with noise (DBSCAN) is a popular density-based clustering algorithm. The main idea behind DBSCAN is to group together points that are close to each other based on a specified distance metric and a minimum number of points required to form a dense region, referred to as "eps" and "minPts" respectively. Unlike traditional clustering algorithms, which are based on a predefined number of clusters, DBSCAN dynamically finds clusters of arbitrary shapes and can identify noise points that do not belong to any cluster. This makes it an attractive choice for finding patterns in large, complex datasets where clusters may not be well-defined or easily noticeable. DBSCAN has the advantage of being able to handle non-linearly separable data, can identify noise points, and can be applied to both spatial and non-spatial data.

Feature Extraction

In this research work, the feature extraction is done using statistical features like mean, standard deviation, kurtosis, and skewness.

Mean

The mean is the average of the numbers provided, and it is computed by dividing the total number of values by the sum of the numbers provided. The mean of a set of values can be calculated for each feature or attribute in the data and used as a new feature. This is mathematically shown in Eq. (1).

$$Mean = \frac{Sum\ of\ all\ observations\ of\ R^{pre}}{Total\ number\ of\ observations\ in\ R^{pre}} \quad (1)$$

$$\bar{y} = \frac{\Sigma y}{z} \quad (2)$$

Where, $\bar{y}$ = mean value, y = Items given, z = Total number of items

The significance of mean resides in its capacity to sum up the entire dataset in a single value.

Standard deviation

The standard deviation is a commonly used statistical measure that describes the amount of variability or dispersion of a set of values. It is calculated as the square root of the variance, which is the average of the squared differences from the mean. The standard deviation is a useful measure in understanding the distribution of data, as it provides information about how spread out the data is from the mean. This is mathematically shown in Eq. (3).

$$SD\ (\sigma) = \sqrt{\frac{\Sigma(R^{pre} - \mu)^2}{N}} \tag{3}$$

Where R^{pre} is the input value (pre-processed data, μ is the mean and N is the total number of elements.

Kurtosis

Kurtosis is a statistical measure that describes the shape of the distribution of a set of values. It is a measure of the "peakedness" or "flatness" of the data compared to a normal distribution. A normal distribution has a kurtosis of zero, while positive kurtosis indicates a more peaked distribution and negative kurtosis indicates a flatter distribution. Kurtosis is commonly used in financial and economic analysis to describe the distribution of returns from investments or financial assets. In these applications, kurtosis is used to assess the risk associated with the investment, as high kurtosis may indicate a higher level of tail risk, or the risk of extreme outcomes, such as large losses. This is mathematically shown in Eq. (4).

$$Kurtosis\ (high\ order) = \frac{4^{th}\ Moment}{4^{th}\ Moment^2} \tag{4}$$

These extracted features are denoted as f^{high}

Skewness

Skewness is a statistical measure that describes the asymmetry of a distribution of values. It measures the extent to which the values are shifted or tilted to one side or the other of the mean. A normal distribution has a skewness of zero, which means that the values are symmetrical around the mean. Positive skewness indicates that the values are shifted towards the right or that there is a long tail on the right side of the distribution, while negative skewness indicates that the values are shifted towards the left or that there is a long tail on the left side of the distribution. Skewness is used to describe the distribution of data and to identify any asymmetries in the data as shown in Eq. (5)

$$skewness = \frac{3(Mean - Median)}{StandardDeviation} \tag{5}$$

Classification

Among the extracted features, the optimal features are selected using a new hybrid optimization model referred as CLAIS, it is the conceptual enhancement of standard Cuckoo search optimization (CSO) and adolescent identity search algorithm (AISA), respectively. The extracted features are passed as an input to the classification phase. Classification can be used to improve agriculture production by dividing data into predefined categories or classes. This technique can help make informed decisions and optimize resource allocation based on the characteristics of the data.

Cuckoo search based Levy adolescent identity search algorithm

Cuckoo search based Levy adolescent identity search algorithm is a novel optimization algorithm developed by Esref Bogar and Selami Beyhan in 2020. It is based on modeling the process of adolescent identity formation and incorporates elements of human behavior into the optimization process. Human intelligence varies from person to person, an adolescent's maturity is entirely dependent on the individual. Most likely, the optimization time interval can vary depending on this behavior. The cost function is the next consideration, meaning that some people may behave differently from others depending on the structure of the community norms. Therefore, taking well-behaved people into account enables one to obtain the optimal cost function. If none of the adolescents arrive at the best value, it is assumed that there is an optimization problem. Therefore, it is a scenario that could arise during the optimization process. To resolve these problems and achieve the identity status of the committed individuals, Marcia's new feature of identity search behaviour has been proposed.

CLAIS implementation

Consider the following, when examining how the CLAIS is applied to the problem of unrestricted single-objective optimization is defined as per Eq. (6),

$$minB\,(b_1, b_2, \ldots, b_n)$$
$$\underline{a}_c \le b_c \le \overline{a}_c, c = 1,2,\ldots,n \tag{6}$$

The objective function is represented as $B(.)$ to be decreased, b_c Indicates the cth decision variable, the decision variable number is indicated by n, $\underline{a}_c$ and $\overline{a}_c$ Indicates the lower and upper bounds on the cth variable, correspondingly.

Random initialization

Inside the boundary of the solution space, CLAIS first generates the initial population at random. The assumption is that there are N adolescents in the group, and that each has n identity characteristics that make them unique. Moreover, the identity of dth adolescent $\{b^d\}\ d = 1,2 \ldots, N$ may be denoted by the vector and can be achieved as per Eq. (2),

$$b_c^d = \underline{a}_c + C(0,1)_c \times (\overline{a}_c - \underline{a}_c), \quad d = 1,2 \ldots, N;\ c = 1,2, \ldots n \tag{7}$$

Where, b_c^d indicates the cth identity attribute of the dth adolescent and $C(0,1)$ represents the equivalently distributed arbitrary number in the interval [0,1]. In the matrix below, the populations, which include all teenagers, are listed according to their unique characteristics as shown in Eq. (8),

$$D = \begin{bmatrix} b_1^1 & b_2^1 & \ldots b_n^1 \\ b_1^2 & b_2^2 & \ldots b_n^2 \\ . & . & . \quad . \\ . & . & . \quad . \\ . & . & . \quad . \\ b_1^N & b_2^N & \ldots b_n^N \end{bmatrix}_{N*n} \tag{8}$$

Where D termed as population index.

Fitness Evaluation

The fitness of each adolescent is evaluated by substituting its identity, represented by the values of the decision variables, into a predefined fitness function. The result of this calculation is the fitness value, which is then stored for each adolescent. This process allows for the comparison of the relative performance of each adolescent and enables the selection of the best individuals for the next generation. The fitness function represents the objective to be optimized, and the goal of the optimization process is to find the values of the decision variables that result in the highest fitness value as per Eq. (9),

$$fit(D) = \begin{bmatrix} fit_1[b_1^1 \ \ b_2^1 \ \ .....b_n^1] \\ fit_2[\ b_1^2 \ \ b_2^2 \ \ .....b_n^2] \\ . \quad . \quad . \quad . \\ . \quad . \quad . \quad . \\ fit_N[b_1^N \ \ b_2^N \ \ .....b_n^N] \end{bmatrix}_{N*1} \tag{9}$$

Where, $fit(D)$ represents current solution population fitness vector.

Create a New Identity

Multiple metaheuristic techniques are used to repeatedly establish new search agents until the predefined termination criteria is satisfied. A numerical model of identity formation is to be pursued.

Case 1

The teen imitates by identifying the best qualities in the group. In particular for the online approximation issues, the Chebyshev functional-link network (CFLN) is the well-specified orthogonal approximation function scheme that has fast and precise approximation capacity. Chebyshev polynomials have orthogonal, recurrence associations and an intense definition duration [-1,1], making them more suitable for approximation functions. For $b \in [-1,1]$, the polynomial of Chebyshev $\{A_l(b)\}_{l=0,1,2,...}$ are produced through the subsequent recurrence as per Eq. (10),

$$A_1(b) := \begin{cases} 1, & : if\ l = 0 \\ b, & : if\ l = 1 \\ 2b\ A_{l-1}(b) - \ A_{l-2}(b) & : if\ l \geq 2 \end{cases} \tag{10}$$

The CFLNs were effectively established and built. The populations of the CFLN scheme are initially normalized between $[-1,1]$ as per Eq. (11),

$$\hat{b}_c^d = 2\frac{(b_c^d - \underline{a}_c)}{(\overline{a}_c - \underline{a}_c)}, d = 1,2, ..., N; c = 1,2, ..., n \tag{11}$$

Given the previous equation, $\hat{b}_c^d$ displays the dth adolescent's cth identity attribute's normalised value. The following matrix Eq. (12) serve as a representation of the normalized inputs.

$$\hat{D} = \begin{bmatrix} \hat{b}_1^1 & \hat{b}_2^1 & .....\hat{b}_n^1 \\ \hat{b}_1^2 & \hat{b}_2^2 & .....\hat{b}_n^2 \\ . & . & . \quad . \\ . & . & . \quad . \\ \hat{b}_1^N & \hat{b}_2^N & .....\hat{b}_n^N \end{bmatrix}_{N*n} \tag{12}$$

$\hat{D}$ denotes the orthogonal function scheme's standardized input matrix. Initially, the regression matrix Ψ and the vector ψ is defined as per Eq. (13), if sub-regressor is indicated for each input variable.

$$\Psi = \begin{bmatrix} \psi_1^1 & ..... \ \psi_n^1 \\ \psi_1^2 & .....\psi_n^2 \\ . \quad . & . \quad . \\ . \quad . & . \quad . \\ . \quad . & . \quad . \\ \psi_1^N & .....\psi_n^N \end{bmatrix}_{N*n} \tag{13}$$

The weighting parameter of the approximation scheme are calculated employing LSE as shown in Eq. (14),

$$\begin{aligned} \hat{e} &= (\Psi^T\Psi)^{-1}\Psi^T B \\ \hat{e} &= [e_1^1 ... e_l^1 ... e_1^n ... e_l^n]^T_{1\times(n\times l)} \\ &= [e^1 ..... e^n]^T \end{aligned} \tag{14}$$

Where $\hat{e}^c \in \Re^{1*l}$ denotes the cth input weight vector.

For every matrix component specified in Eqn. (12), the partial fitness value is achieved by employing Eq. (15) and saved as in Eq. (16),

$$\hat{B}_c^d = \psi_c^d e^d \tag{15}$$

$$\hat{B}_f = \begin{bmatrix} \hat{B}_1^1 & \hat{B}_2^1 & .....\hat{B}_n^1 \\ \hat{B}_1^2 & \hat{B}_2^2 & .....\hat{B}_n^2 \\ . & . & . \quad . \\ . & . & . \quad . \\ \hat{B}_1^N & \hat{B}_2^N & .....\hat{B}_n^N \end{bmatrix}_{N*n} \tag{16}$$

The values in the population matrix (D) described in Eq. (12) are equivalent to row indices in each and every matrix column in Eqn. (16), and the optimal identity vector of the current population can be established as per Eq. (17),

$$b_c^* = b_c^{g^c}, g^c = arg\ \ min\{\hat{B}_c^L | L = 1,2,3, ..N^L\ \}, \forall c \tag{17}$$

In the first instance, the dth adolescent's new identity (b_{nw}^d) is assessed as per Eq. (18),

$$b_{nw}^d = b^d - h_1(b^d - b^*) \tag{18}$$

A random number in the interval $[0,1]$is represented by the equation h_1 in the above sentence. By first estimating the identity attributes of the peers, determine the set of the best identity attributes, which is indicated by b^*.

Case 2

Identity is created by imitating the powerful, prestigious, and successful role model. As per the proposed Eq. (19), it reaches a novel identity for the adolescent.

$$b_{nw}^d = b^d - h_2(b^i - b^{hg}) \oplus Levy(\beta) \tag{19}$$

The Cuckoo based Levy flight is used in this algorithm to diversify the search and avoid premature convergence, which is when the search prematurely terminates before finding the optimal solution. The Levy flight allows the optimization algorithm to jump to distant regions in the search space, increasing the likelihood of finding the global optimum. By randomly selecting the next solution from the tail of the Levy distribution, the algorithm can explore a wider range of solutions, reducing the risk of getting stuck in local optima. The random number in the interval $[0,1]$

is represented as h_2 and the role model or the optimum individual is represented as b^{hg}. For $i \neq hg, b^i$ represents the ith adolescent. $(b^i - b^{hg})$ is similar to cooperative search (CS) and is employed to prevent immature convergence.

Case 3

The teenager adopts undesirable identity traits, such as substance abuse, smoking, immature sexual behavior, etc. Let's assume that the component from the population matrix that was arbitrarily chosen is represented by the negative identity attribute (b^z). The new identity of the dth adolescent is defined. By Levy flight, new state is calculated as per the proposed Eq. (20),

$$b^d_{nw} = b^d - h_3(b^d - b^s) \oplus Levy(\beta) \quad (20)$$

Cuckoo based Levy CLAIS enhances the exploration strategy, leading to a greater diversity of solutions. This increased diversity increases the chances of finding the optimal solution more efficiently. The goal of CLAIS is to improve the exploration strategy, which results in a better solution through a more diverse set of solutions. $\oplus$ means entry-wise multiplication, row vector of uniformly distributed number in the range $[0,1]$ is represented by h_3. b^s represents the negative identity vector as shown in Eq. (21).

$$b^s = [b^z \quad b^z \quad \ldots\ldots b^z]^A_{1*n} \quad (21)$$

As a result, three cases are combined to serve as and shown in Eq. (22),

$$b^d_{nw} = \begin{cases} Case\ 1: & b^d - h_1(b^d - b^*) & h_4 \leq 1/3 \\ Case\ 2: & b^d - h_2(b^i - b^{hg}) & 1/3 < h_4 \leq 2/3 \\ Case\ 3: & b^d - h_3(b^d - b^s) & 2/3 < h_4 \end{cases} \quad (22)$$

h_4 represents the random number in the range $[0,1]$ employed as the selection strategy.

The algorithm has been thoughtfully created to have various search capabilities. When b^* is accurately estimated, the first case serves the algorithm's exploitation characteristic. New solutions are found between the minimum and maximum values of variables in the current population, regardless of the model's estimated values. In the second scenario, the emphasis is on exploitation and there is a tendency to choose the best course of action (the role model). Additionally, b^d prevents the immature convergence. The first two cases have been created in order to test the algorithm's potential for use. The third case, however, adds the ability to conduct exploration to eliminate the regional minima.

Mechanism of Boundary Control

The boundary control method is activated when the new person leaves the designated search space. In the absence of such variations, the variables violate their restricted interval. The violators are then arbitrarily established under their restricted interval. A boundary control mechanism is triggered if a brand-new person leaves the search space. The variables that deviate from their limit range are subject to Eq. (7) and are located at random within their limit range. This mechanism is the same as that suggested in the backtracking search optimization algorithm (BSA), which is very successful in achieving population diversity that makes it possible for searches to be effective in both the present and future generations.

Updating mechanism

Whether the new identity is accepted into the population is determined by the updating mechanism. The fitness value of the adolescent's new identity is calculated before the updating mechanism is used. The current identity is then removed from the population and the new one is introduced in its place if the new identity is superior to the current one. For each brand-new identity, the same process applies. As a result, the searchers develop to use in gradual evaluation. A common updating mechanism used by many metaheuristics occurs at the conclusion of each iteration. At every evaluation, CLAIS, however, employs the updating mechanism. By immediately introducing a more capable solution into the population, this improves other solutions.

Stopping/termination criterion

In general, optimization algorithms finish the task of searching using one or a combination of four different stop criteria, such as function tolerance, the maximum number of function evaluations, the maximum run time, and the maximum number of iterations. The maximum number of iterations is taken into consideration as the termination criterion in the current study, which links the adolescent years to an iterative process and denotes the ending of puberty.

CLAIS based DQN

The proposed CLAIS-DQN model is designed to tackle farming issues in agriculture by using a hybrid meta-heuristic-based duel DQN algorithm. This model performs self-driven clustering to address clustering problems. It analyzes various factors such as air temperature, air humidity, soil moisture, soil temperature, and rain level to determine the climate that yields the highest production. Additionally, it monitors water flow to the plants to ensure their proper growth and can provide additional water if the prediction shows that water flow is low. A set of goal-oriented algorithms known as reinforcement learning can be used to teach software agents how to behave in a specific environment in order to maximize the cumulative reward. Based on reinforcement learning, agents can discover an ideal course of action for sequential decision-making issues in a variety of fields. The applicability of reinforcement learning algorithms is restricted to domains with readily available handcraft features or low-dimensional state spaces that are completely observed despite the fact that these algorithms have been successful in a variety of domains. Q-Learning is a model-free reinforcement learning algorithm that is used to learn a policy, telling an agent what action to take under what circumstances. It estimates the optimal action-value function, also known as the Q-function, which gives the expected return (discounted future rewards) for taking a certain action in a certain state and following the optimal policy thereafter. The algorithm updates the Q-function estimates iteratively based on observed experiences, eventually converging to the optimal policy.

A deep Q network (DQN) is a newly created end-to-end reinforcement learning agent that works similarly to the Qtable in Q-learning by using a DNN to map the relationships between actions and states. The more effective replacement for dynamic programming (DP) is reinforcement learning (RL). By repeatedly observing the current state st, the appropriate action ac, the new state st′, and the reward re, Q-learning, the model-free approach in RL, determines the best course of action. As per Eq. (23), Q-learning updates the Q-value.

$$Q^{new}(st_i, at_i) \leftarrow (1-\alpha)Q(st_i, at_i) + \alpha(re_t + \gamma\max_{ac} Q(st_{i+1}, ac)) \tag{23}$$

The learning factor determines the old Q-value and the predicted Q-contribution values to the new value. The old Q-value makes up the first component, and the reward plus discounted future values make up the second. Future values and reward sums are the new value alone if is one. If is zero, the new Q-value is equal to the old Q-value. Qlearning is based on greedy selection; it always chooses the course of action with the highest potential reward, which can trap the optimization in local minima by choosing the same maximum value repeatedly. The phase is known as exploitation. In order to converge the optimization into global minima, an exploration factor is required. This shown in Eq. (24) as,

$$Action\ ac = \begin{cases} \max_{ac} Q(st, ac) \forall\ R > \varepsilon \\ Random\ ac\ \forall R \leq \varepsilon \end{cases} \tag{24}$$

First, two crucial elements of the DQN architecture are covered: experience replay and the target network. By using experience replay, the DQN network has the advantage of avoiding the convergence into local minima. The replay memory contains the state-action pairs that have been used thus far: st, ac, st′, and ac′. DQN randomly samples the prior experiences to obtain the highly uncorrelated data at the input rather than introducing the most recent transition into the network. Utilizing sequential feedback would cause correlated values to be at the input, increasing the likelihood of encountering local minima.

The neural network in DQN aims to minimize the mean square error. The loss function is with the neural network weight.

$$Lo_t(\theta_t) = \mathbb{E}_{st,ac\sim\rho()}[(tn_t - Q(st, ac; \theta_t))^2] \tag{25}$$

Where tn_t is the target network, $Q(st, ac; \theta_t)$ is the predicted Q- values. The target network is reformulated as shown in Eq. (26), for the weights of the previous iteration θ_{t-1}.

$$tn_t = \mathbb{E}_{st',\sim\varepsilon}[re + \gamma\max_{ac'} Q(st', ac'; \theta_{t-1})] \tag{26}$$

For stochastic gradient optimization in the neural network, the weights from the previous iteration are held constant while taking the derivative as per Eq. (27).

$$\nabla_{\theta_t} Lo_t(\theta_t) = \mathbb{E}_{st,ac\sim\rho()}[(re + \gamma\max_{ac'} Q(st', ac'; \theta_{t-1}) - Q(st, ac; \theta_t))\nabla_{\theta_t} Q(st, ac; \theta_t)] \tag{27}$$

Due to the fact that network weights are dependent on the target network and that they fluctuate with each iteration. Therefore, it is impossible to reduce losses in a shared network with unstable and dynamic targets. DQN uses a different neural network to estimate the target in order to lessen this.

Result and Discussion

To implement the proposed model, PYTHON has been used. Dataset1 and Dataset2 were used to gather the information for the evaluation. In this part, the performance of the suggested strategy is contrasted with that of widely used techniques like adolescent identity search algorithm (AISA), rainfall optimization (RFO), deep belief network (DBN), and convolutional neural network (CNN).

Dataset Description

Intelligent irrigation system

The "Intelligent Irrigation System" dataset refers to a collection of data related to the irrigation of crops. It likely includes information on various environmental and soil conditions, water usage, and the performance of the irrigation system. This data can be used to optimize irrigation practices, improve crop yield, and conserve water resources. This dataset is to generate an intelligent irrigation system that measures the moisture of soil and helps to take the decision to turns on or off the water supply. The aim of this dataset is to provide an irrigation system that is automatic for the plants so it helps in saving wat

Smart agricultural production optimizing engine

The "Smart agricultural production optimizing engine" dataset refers to a collection of data used to optimize agricultural production. This data likely includes information on environmental conditions, soil characteristics, and crop performance. The goal of the dataset is to improve agricultural productivity to make informed decisions about crop management and resource allocation. Concerns about food security, population growth, and climate change have prompted the industry to look for more creative ways to increase crop yield. However, the current COVID-19 crisis has highlighted the agricultural sector's vulnerability and raised concerns about how to sustainably meet the world's food demand in light of the relevant negative factors. Once more, efficiency is the key to finding a solution because it allows us to do more with less.

Performance metrics

A number of metrics are used to measure the performance, including F-measure, FPR, specificity, NPV, accuracy, MCC, sensitivity, FNR, and recall.

- *Sensitivity*

Simply divide the total positive aspects by the percentage of real positive forecasts to get the critically appraised.

$$Sensitivity = \frac{TP}{TP + FN}$$

- *Specificity*

The degree of specificity is calculated by dividing the total number of correctly predicted negative outcomes by the total number of negatives.

$$Specificit\ y = \frac{TN}{TN + FP}$$

- *Accuracy*

The accuracy is defined as the ratio of correctly classified material to all of the information in the log. The accuracy is described as follows:

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

- *Precision*

By employing the entire number of samples used in the classification process, precision is the representation of the total number of genuine samples that are appropriately taken into consideration during the classification process.

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

- *F-measure*

The harmonic mean of recall rate and accuracy is how the F-measure is defined.

$$F_{Measure} = \frac{2\ Precision\ \times Recall}{Precision + Recall}$$

- *NPV*

NPV describes the effectiveness of a diagnostic test or other quantitative metric.

$$NPV = \frac{TN}{TN + FN}$$

- *MCC*

MCC is a two-by-two binary variable association assessment.

$$MCC = \frac{(TP \times TN - FP \times FN)}{\sqrt{(TP + FN)(TN + FP)(TN + FN)(TP + FP)}}$$

- *False positive ratio*

The false positive rate (FPR) is determined by dividing the number of bad outcomes by the number of negative events that were incorrectly classified as favorable (false positives).

$$FPR = \frac{FP}{FP + TN}$$

- *False negative ratio*

The false-negative rate (FNR), also recognized as the "miss rate," is the probability that a real positive will be missed by the test.

$$FNR = \frac{FN}{FN + TP}$$

Overall Performance Analysis of the Projected Model

The proposed approach's effectiveness has been investigated, and the outcomes have been analyzed with those of existing techniques like AISA, RFO, DBN, and CNN. Table 1 explains the comparison method among the models for dataset 1.

Table 1: Testing metrics: Classification: Dataset 1

Performance metrics	*AISA*	*RFO*	*DBN*	*CNN*	*CLAIS*
Accuracy	0.821629	0.871398	0.891795	0.882126	0.955690
Precision	0.787024	0.864226	0.935854	0.874875	0.947824
Sensitivity	0.863613	0.878726	0.844781	0.889554	0.963727
Specificity	0.780201	0.864168	0.938187	0.874796	0.947760
F-measure	0.796928	0.844247	0.861888	0.854650	0.925913
MCC	0.827131	0.916205	0.883180	0.921036	0.934493
NPV	0.863079	0.878716	0.855989	0.889523	0.963716
FPR	0.024652	0.021580	0.021523	0.026940	0.020953
FNR	0.006604	0.003782	0.004456	0.010238	0.003672

Table 2: Testing metrics: Classification: Dataset 2

Performance metrics	*AISA*	*RFO*	*DBN*	*CNN*	*CLAIS*
Accuracy	0.864314	0.849846	0.857947	0.890193	0.964431
Precision	0.907015	0.814052	0.850885	0.882876	0.956492
Sensitivity	0.818748	0.893272	0.865161	0.897689	0.972541
Specificity	0.909276	0.806995	0.850828	0.882797	0.956429
F-measure	0.835328	0.824296	0.831215	0.862467	0.934381
MCC	0.855964	0.855537	0.902062	0.929460	0.943040
NPV	0.829611	0.892719	0.865152	0.897659	0.972530
FPR	0.020859	0.025498	0.022393	0.027186	0.021145
FNR	0.004319	0.006831	0.003925	0.010332	0.003706

Table 1, shows the comparison of the effectiveness of testing metrices for classification based on dataset1. The models include AISA, RFO, DBN, CNN, and proposed CLAIS. Accuracy, precision, sensitivity, specificity, F-measure, MCC, NPV, FPR, and FNR are among the criteria. The greatest accuracy value was 0.9556 for the CLAIS optimization algorithm, while the least amount was 0.8216 for the AISA model. CLAIS recorded the highest precision with a score of 0.9478, while the CNN had the lowest score of 0.8748. As a whole, the suggested framework performed the best, accompanied by the CLAIS model. On analyzing the acquired outcomes, it's clear that the projected model has recorded the lowest FPR and FNR as 0.020 and 0.003, respectively, which is the least value.

As per Table 2, the analysis on the proposed model with classification for dataset is described. It compares the proposed method with the existing methods, namely, AISA, RFO, DBN, CNN, and proposed CLAIS. The proposed model attains the highest accuracy as 0.9644 as all the existing model attains lower values. For FPR and FNR, the proposed

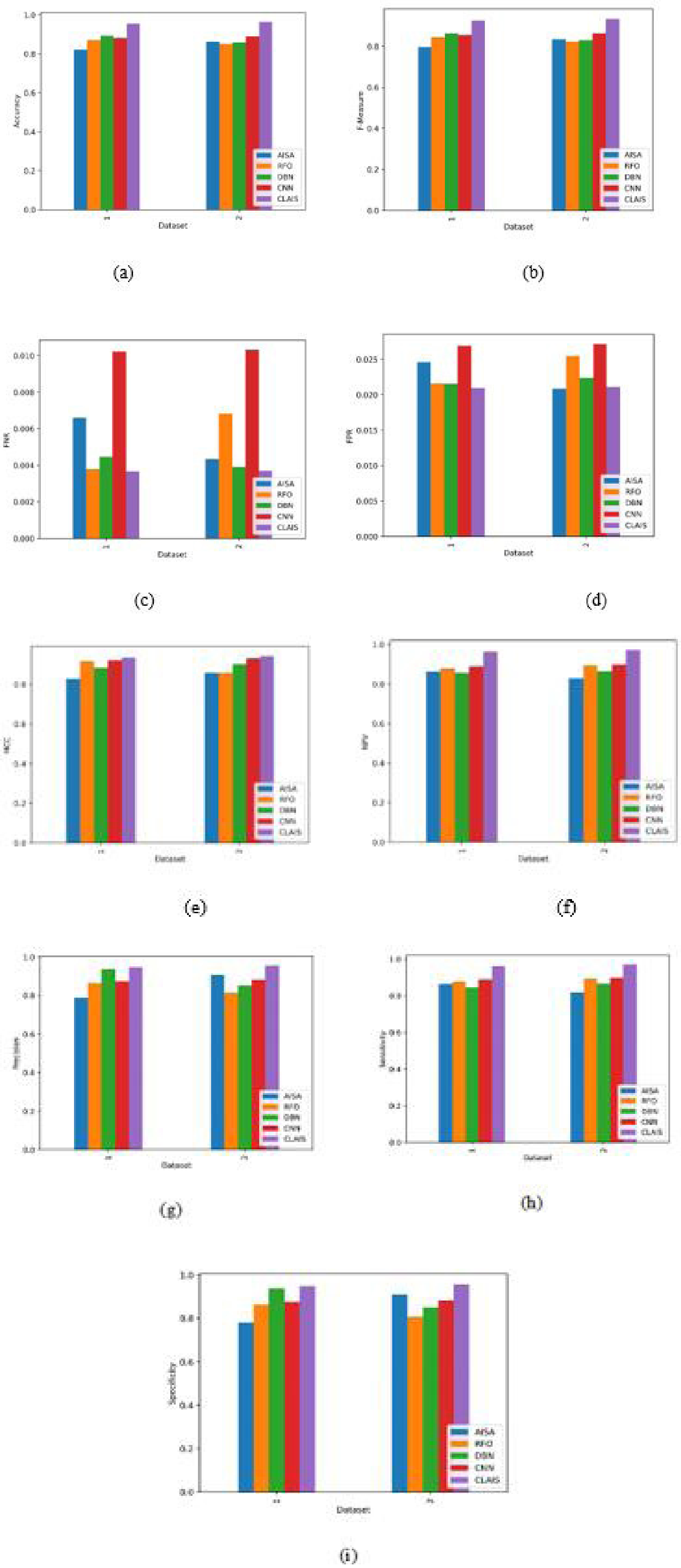

Figure 2: Graphical representation: Classification (a)Accuracy (b)F-Measure (c)FNR (d)FPR (e)MCC (f)NPV (g)Precision (h)Sensitivity (i)Specificity

model achieved the lowest values as 0.021 and 0.003, respectively, compared to all the existing models.

The graphical representation of overall performance analysis of metrics like accuracy, F-measure, FNR, FPR, MCC, NPV, precision, sensitivity, and specificity for dataset1 and dataset2 among the models based on the classification is shown in Figure 2.

Conclusion

In this research work, an innovative enhancing agricultural production model was developed. In agriculture, irrigation was a crucial aspect for providing water to crops based on the soil type. Evaluating soil fertility, temperature, rainfall, and setting irrigation schedules was important for success in farming. To enhance agricultural production, an IoT-based hydration system that used soil moisture and humidity sensors to monitor soil conditions and water crops precisely was developed. This system effectively managed water usage in farming, resulting in an efficient conservation of water resources. The proposed model was divided into four main stages: pre-processing, clustering, feature extraction, and classification. Raw data was first pre-processed through a data cleaning process. Then, the DB scan algorithm was used to cluster the data. Statistical features such as mean, standard deviation, kurtosis, and skewness were used to extract important features from the clustered data. The optimal features were selected using a new hybrid meta heuristic optimization model referred as CLAIS algorithm. The projected CLAIS model was the conceptual amalgamation of the standard CSO and AISA, respectively. CLAIS-based deep Q network (CLAIS-DQN) classifier was used to classify the optimal features and improve the overall performance of the network through efficient request offloading. The proposed model was implemented using PYTHON and achieved the highest detection accuracy of 96%.

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