ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20240404001447
Original scientific paper

Blockchain-Integrated Deep Reinforcement Learning for Secure Data Sharing in Precision Agriculture

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Abstract: In Precision Agriculture (PA), the need to create a safe and intelligent building prompts the integration of blockchain technology with Internet of Things (IoT)-based systems. This paper proposes a deep reinforcement learning-based prediction and Blockchain-based Secure Data Sharing system for PA. The major objective is to apply blockchain technology to enable safe data sharing in the PA space. IoT sensors first collect data on important characteristics including weather, temperature, humidity, crop health, and soil moisture. Then, the collected data are pre-processed by z-score and Decimal Scaling normalization techniques. Then, the pre-processed data are analyzed and clustered by the Balance Iterative Reducing and Clustering utilizing Hierarchies (BIRCH) technique. It is a scalable and efficient algorithm for clustering large datasets. Next, the features are extracted by Convolutional Neural Networks (CNN). CNNs have independent feature learning and powerful computing ability, and it improves the accuracy and automation of extraction. After the feature extraction, the optimal features are selected by Hybrid Red Deer and Dwarf Mongoose Optimization (H-RDMO). For prediction, an Attention-based Recurrent Neural Network is utilized, which gives accurate predictions on sequential data and then the Hybrid Deep Reinforcement Learning approach (Hybrid deep Q-learning and policy gradient model) is used for the accurate disease classification. Finally, Hybrid Modified ECC with ElGamal encryption technique is used to ensure data security during sharing. It provides a robust and efficient cryptographic solution with enhanced security features. The suggested model is implemented using the PYTHON programming language, and its performance is assessed employing metrics such as F-score, recall, specificity, precision, sensitivity, accuracy, MCC, NPV, FPR, and FNR. Suggested optimized H-RDMO achieves higher accuracy (98.4%) and precision (97%) compared to current techniques and the ESMECC-Elg achieves the Energy consumption of 150 J.

Keywords: attention based RNN; data sharing; egret swarm optimization; IoT technology; precision agriculture

1 INTRODUCTION

PA, often denoted as precision farming, is a farming method that optimizes many elements of crop production by using technology like drones, sensors, data analytics and GPS [1]. To make better-educated decisions regarding planting, fertilizing, watering, and harvesting crops, it requires gathering data on particular fields [2]. With the use of data, farmers may customize their operations to the unique circumstances of their fields, leading to greater productivity, less resource consumption, higher crop yields, and fewer negative environmental effects. Farming is the main source of gross domestic product (GDP) and food, making up 6.4% of the world economy. Nine nations throughout the world rely heavily on agriculture as a source of income. Fuel and jobs are provided by agriculture to millions of people. With the use of technology like GPS, sensors, and data analysis, PA maximizes agricultural methods and increases productivity through site-specific management [3]. It uses AI with Deep Learning (DL) integration to automate processes and generate insights at scale, enhancing crop yields and resource efficiency [4].

PA could gain greatly from the increased data integrity, transparency, and traceability that blockchain-based secure data exchange provides [5]. In addition to promoting smooth collaboration and confidence among stakeholders, it makes irreversible record-keeping possible, which lowers conflict and guarantees dependability. However, difficulties including restrictions on scalability, complicated regulations, and privacy concerns prevent wider implementation [6]. To fully realize blockchain's detrimental potential, overcoming these challenges requires creative solutions and industry collaboration [7]. Through the resolution of scaling concerns, adept navigation of regulatory frameworks, and the incorporation of resilient privacy protocols, the agriculture industry may fully leverage blockchain technology [8]. This development has the potential to improve agricultural productivity, encourage sustainable practices, and address the problems associated with food security in a global community that is becoming more linked [9]. The key data characteristics collected by IoT sensors in the precision agriculture are Soil moisture level, Temperature, Humidity, Crop health, and Soil nutrient level.

The field of precision agricultural research has explored the potential uses of deep learning and blockchain technology in a range of disciplines, including supply chain management, data sharing, and smart contract implementation [10]. These studies highlight how incorporating these technologies might improve agricultural operations' efficiency and sense of confidence [11]. Investigators want to enhance decision-making processes, guarantee transparency throughout the agricultural value chain, and optimize resource allocation by leveraging deep learning's analytical powers and blockchain's decentralized ledger [12]. Using deep learning algorithms for crop monitoring and yield prediction, utilizing blockchain for safe data sharing among stakeholders, and putting smart contracts into place for automated transactions and contract enforcement are a few examples [13]. These initiatives show the viability and advantages of combining deep learning and blockchain technology with PA, opening up the possibilities for creative solutions that satisfy the changing demands of the industry while fostering resilience and sustainability in farming methods [14].

2 LITERATURE REVIEW

PA aims to monitor and forecast vital parameters like soil condition, irrigation, fertilizer, ambient temperature and moisture and water quality to increase crop yield, and was explored by Bhanumathi and Kalaivanan [15] in 2019. This was accomplished by combining IoT with geographic technology. The accurate prediction of fertilizer, weed, and irrigation needs as well as decision-making regarding all supply and control aspects of farming can be anticipated with the use of geospatial and IoT in smart farming.

Gawande et al., [16] investigated how precision agricultural technologies may help achieve environmentally responsible and sustainable agriculture in 2023. Precision farming enhances crop management and boosts yield by permitting farmers to make well-versed decisions based on real-world data. It accomplishes this by utilizing state-of-the-art tools including data analytics, remote sensing, GIS, and GPS.

A DL based framework for weed detection (eggplant, also known as brinjal) was proposed in 2023 by Patel et al. [17]. YOLOv3, Faster RCNN, ResNet-18, and CenterNet are employed in the suggested study. This study's main goal was to separate plant parts from non-plant (weed) sections in crop pictures. Weeds may be accurately located from images by using object detection. The suggested model uses a hybrid technique of item detection and classification.

A deep learning neural network and IoT-empowered intelligent irrigation model for PA (DLiSA) was provided by Kashyap et al. [18]. DLiSA forecasts the volumetric soil moisture content, the length of the irrigation period, and the spatial distribution of water required to irrigate the arable land using a long short-term memory network (LSTM). The simulation's findings show that, in the experimental farming region, DLiSA uses water more efficiently than cutting-edge models.

In 2022, Akhter and Sofi [19] summarized the influence and promise of computation practices including machine learning (ML) in IoT, data analytics, agriculture and wireless sensor networks. A suggested technique leverages data analytics and ML in Internet of Things devices to forecast apple disease in apple orchards in Kashmir Valley. Furthermore, a survey was conducted in the region to collect data from farmers on new technology and how they could affect precision farming.

The performance of state-of-the-art (SoA) CNN based object identification frameworks in identifying nuisance insects that resemble beetles on heterogeneous outdoor images taken by different sources was investigated by Butera et al. [20], in 2021. Creating a foundational model for such undertakings is the aim of this effort. The outcomes show that the current SoA models are suitable for this use case, highlighting the fact that Faster RCNN offers an excellent foundation for inference execution latency and accuracy when paired with a MobileNetV3 backbone.

The agricultural Internet of Things (IoT) system was developed by Jin et al. [21] in 2020. It gathers meteorological data and provides early weather information, enabling the best planning and control of sustainable agricultural output. Because the data are continuously containing complex nonlinear interactions with several factors, it is challenging to make accurate predictions about the future trend. The weather data were split into four variables, and the gated recurrent unit (GRU) networks were trained as the sub-predictors for each element using a serial approach.

Anantraj [22] examined through direct communication from the rancher to the client, the suggested blockchain-based horticulture web application that helps ranchers ensure more significant benefits in 2021. Designed to prevent information from changing while being sent, this application erodes the foundation of blockchain innovation. Business correspondence benefits from this aid and the framework becomes more transparent. On all frameworks across a value chain, squares of time-stepped item peculiarities are stored. Reliably delivering horticultural products and building trust between consumers and ranchers are two benefits of blockchain technology.

Kumar et al. [23] introduced a novel IoT-enabled IA system in 2022, which makes use of deep learning and smart contracts to facilitate safe data sharing across its numerous entities. Specifically, to guarantee safe data transfer in IoT-enabled IA, first create new authentication and key management schemes. The CS uses a revolutionary deep learning architecture to assess and further detect breaches using the encrypted transactions. In CS, a peer-to-peer network of CSs carries out the consensus mechanism based on smart contracts (SCs) on legitimate transactions, validating and adding the generated blocks to the blockchain.

In 2021, Anand [24] presented a novel method based on wireless sensors, such as temperature and moisture sensors, for adaptive water scheduling in PA. The suggested system makes use of blockchain technology to provide safe cloud data transfer. Furthermore, the improved LEACH algorithm achieves energy-efficient data transport. The PIC microcontroller module is utilized to gather sensor data. The Raspberry Pi module is then utilized to send collected data to cloud. Next, an IoT approach based on blockchains is utilized to protect and validate this data.

3 THE PROPOSED METHOD

Blockchain and deep learning are used in PA to provide safe data exchange for all parties involved. Data integrity is guaranteed by blockchain technology, which creates an immutable ledger that cannot be changed without agreement. Blockchain protects shared data in precision agriculture (PA), preserving accuracy and dependability. It uses cryptography and consensus to share data securely, decentralizes to foster trust, and uses smart contracts to automate agricultural processes, cutting down on human interference and increasing productivity. It entails combining deep learning algorithms for data analysis and insight extraction with blockchain technology, which offers transparent and unchangeable record-keeping. This method facilitates easy cooperation while improving the traceability, transparency, and integrity of shared agricultural data. Important information on weather patterns, crop health, soil conditions, and other topics is gathered via IoT devices. Preprocessing methods like decimal scaling normalization and z-score normalization are applied to this data. Attention-based Recurrent Neural Networks (RNN) and reinforcement learning techniques are used for detection and classification after clustering, feature extraction, and selection. In the end, PA techniques are optimized by security methods as Egret Swarm Optimization with Modified ECC and ElGamal (ESMECC-Elg) encryption, which guarantee the veracity and privacy of shared data.

Fig. 1 depicts overall architecture of the suggested methodology.

- Z-Score Normalization: It ensures data integrity by creating an unchallengeable record through Blockchain technology. Data is converted into a standard normal distribution with mean of 0 and standard deviation of 1. This technique is useful when dealing with data predicted to follow a Gaussian distribution, enabling evaluation and analysis across various scales.
- Decimal Scaling normalization: It aligns values between –1 and 1 by dividing by a power of 10 from the dataset's largest absolute value, ensuring scale consistency for further processing when data range varies.
- Clustering Algorithm (BIRCH): It is designed for handling large datasets efficiently, crucial for real-time processing in precision agriculture with IoT sensor data. BIRCH's hierarchical clustering can reveal hierarchical data features and assist in identifying clusters with varying granularity in agricultural data. BIRCH is memory-efficient compared to some algorithms, making it suitable for low-power systems like IoT setups.

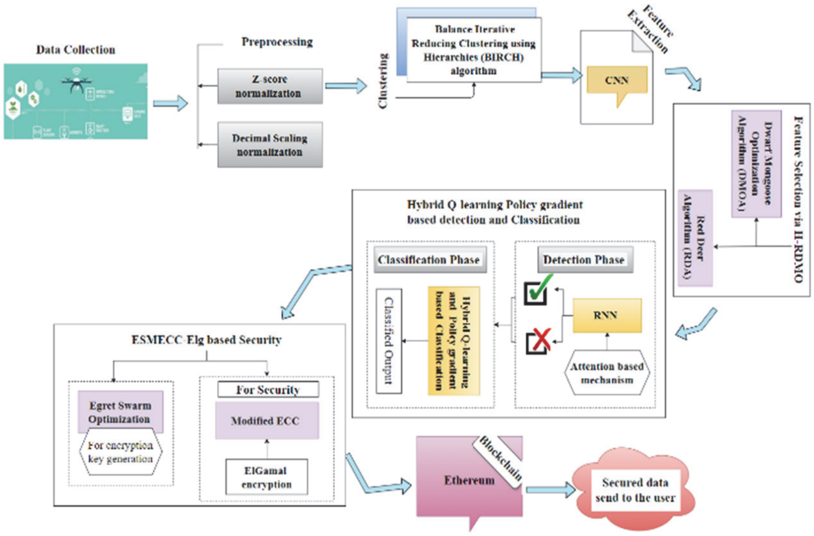

Figure 1 Overall architecture of the proposed methodology

3.1 Balance Iterative Reducing and Clustering Utilizing Hierarchies (BIRCH) Algorithm

An approach for clustering data intended for large-scale datasets is called BIRCH. A technique called *CF*-tree (Clustering Feature Tree) compactly describes clusters by reducing information to *CF* objects with radius, variables, and centroid. Hierarchical clustering of BIRCH structures creates a tree-like structure. This hierarchy represents organizations in a condensed way and allows effective data categorization. BIRCH is beneficial in Precision agriculture for large-scale and streaming information programs. It preprocesses statistics by incrementally clustering data and maintains a hierarchical structure while balancing clustering quality and resource consumption. By gradually constructing a hierarchical clustering structure and lowering the dataset's dimensionality, it effectively clusters data. In order to generate a global clustering solution, BIRCH works iteratively, forming a number of subclusters and combining them. BIRCH is appropriate for real-time data processing because of its hierarchical approach, which allows it to manage datasets of various sizes and types. BIRCH provides scalability and stability by balancing the computational load and memory utilization, which makes it an important tool for a number of applications, such as data mining, pattern recognition, and machine learning. First, provide a fundamental definition. Fig. 2 shows the clustering phase.

Figure 2 Clustering using BIRCH algorithm

Assume that a cluster of N data points is represented by the notation $\left(\bar{X}_i,\ i = 1,\ 2,\ \ldots,\ N\right)$. The following Eq. (1), Eq. (2) and Eq. (3) are the metrics displayed for a single cluster.

$$\text{Center point } \bar{X}0 = \frac{\sum_{i=1}^{N} \bar{X}_i}{N} \tag{1}$$

$$\text{Radius } R = \left(\frac{\sum_{i=1}^{N} \left(\bar{X}_i - \bar{X}0 \right)^2}{N} \right)^{\frac{1}{2}} \tag{2}$$

$$\text{Diameter } D = \left(\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} \left(\bar{X}_i - \bar{X}0 \right)^2}{N\left(N-1\right)} \right)^{\frac{1}{2}} \tag{3}$$

For the metrics of the two clusters, primarily employ the center point Euclidean Distance

$D0 = \left(\left(\bar{X}0_1 - \bar{X}0_2\right)^2\right)^{\frac{1}{2}}$. Birch is a clustering technique that minimizes I/O overhead by just scanning the dataset once and using minimum memory resources to achieve high-quality clustering of large-scale data datasets. A Clustering Feature Tree (*CF* Tree) is a B + tree structure that is similar to the one used by Birch for clustering. Fig. 3 illustrates the three distinct types of nodes: internal, leaf, and root nodes. Several Clustering Features (*CF*s) make up each node. Every node, including leaf nodes, has several *CF*s.

A doubly linked list connects each leaf node, and a pointer to the child node is stored in the internal node's *CF*. Every *CF* can be represented as a triple (*N*, *LS*, *SS*). *LS* is the total of all the data points in the cluster, and *N* is the number of sample points in the cluster.

Eq. (4) is the expression that comes after.

$$LS = \sum_{i=1}^{N} \bar{X}_i \tag{4}$$

The total squares of all the data points within a group of cluster are called *SS*, expressed in Eq. (5).

$$SS = \sum_{i=1}^{N} \bar{X}_i^{\,2} \tag{5}$$

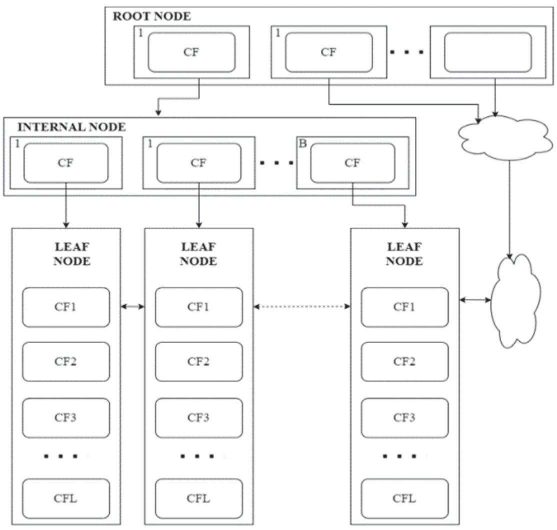

Figure 3 *CF* tree structure

Three parameters are important for the *CF* Tree. The maximum *CF* number *B* for every internal node is the first. The maximum *CF* number *L* for each leaf node is the second. The third one relates to the maximum sample radius threshold ts of each *CF* in the leaf node, or the sample point within a *CF* in the leaf node. Essentially, each sample point in this *CF* must lie within a radius of less than ts around a hypersphere.

3.2 Feature Selection using Hybrid Red Deer and Dwarf Mongoose Optimization (H-RDMO)

The red deer population accommodates men referred to as stags and ladies as hinds, with most effective stags decided on for certain sports. After displaying loud and combative conduct, stags shape harems where a harem refers to a group of hinds led by means of a male. Stags distribute harems based totally on capabilities like vocalization, combating prowess, and bodily attributes, mirroring the idea of health price in Genetic Algorithms (GA). This value publications decision-making for the duration of fights, corresponding to optimization methods in algorithms. The triumphing stag profits get right of entry to a percentage of hinds within each harem, simulating the propagation of answers in GAs via generations. This conduct, corresponding to meta-heuristic algorithms, displays an ongoing method of growth, development, and diversification, crucial for evolutionary achievement. The dynamic interplay among stags and hinds at some point of mating mirrors optimization methods seen in computational algorithms, underlining nature's parallel to algorithmic optimization strategies.

Creating the first Red Deer breed.

Optimization is to identify the most optimal solution depending on variables. An array of variable values is created for the purpose of optimization. In the GA language, the array is commonly referred to as "chromosome," although it is denoted as "*R*" in this context. The solution's counterpart is denoted as *R*. In an optimization problem with n dimensions, a Red Deer can be represented as an array with dimensions $1 \times n_{\text{dim}}$. The definition of this array is represented by Eq. (6).

$$R = \left[X_1, X_2, ..., X_{n_{\text{dim}}}\right] \tag{6}$$

The value of each *R* function, denoted as *fn*, can be computed using Eq. (7).

$$f = fnR = fn\left(X_1, X_2, ..., X_{n_{\text{dim}}}\right) \tag{7}$$

The optimization process commences with a population of size n_p. The values of n_m and n_h are selected for the number of males and the number of females, correspondingly.

A red deer's male roar.

In this stage, male Red Deer vocalize in order to obtain favor. When male Red Deer exhibit superior performance in objective functions compared to their predecessors, they proceed to replace them. All male Red Deer should be permitted to change their postures. Females are drawn to soaring male Red Deer.

Selecting γ, % of superior male Red Deer as leaders.

The male Red Deer exhibits significant variation. Individuals exhibit varying degrees of success. Men have distinct functions in nature; certain individuals engage in harems. Male Red Deer can be classified into two distinct categories: commanders, denoted as *C*, and stags, denoted as *s*. The number of male commanders is correlated with γ, leading to Eq. (8).

$$n \cdot m \cdot C = r\{\gamma \cdot n_m\} \tag{8}$$

A multitude of males are appropriating harems. The most superior male Red Deer is selected, while the remaining ones are referred to as stags. The calculation of the number of stags is determined using Eq. (9).

$$n \cdot s = n_m - n \cdot m \cdot C \tag{9}$$

In male populations, the Stag numbers are denoted as $n \cdot s$.

Stags versus male leaders.

Males engage in random combat with stags for every commander. Determine whether the objective function exhibits superiority over its predecessors.

Make harems

This stage gives rise to harems. A harem is a collective of females that are enslaved by a male leader. The quantity of hinds within harems is contingent upon the prowess of male commanders, encompassing both vocalization and combat. The division of hinds is distributed proportionally to male commanders in order to establish harems. The Eq. (10) defines the normalized value of a male commander.

$$N_v = \upsilon_v - \max_i \{\upsilon_v\} \tag{10}$$

The value and normalized value of the nth male commander is denoted as N_v. In Eq. (11), the normalized power of each male commander is calculated by taking the normalized value of all male commanders.

$$Por_v = \left| \frac{N_v}{\sum_{0=1}^{n \cdot m \cdot c} N_i} \right| \tag{11}$$

From an alternative standpoint, the concept of a male commander's normalized strength pertains to the proportion of hinds that they are expected to possess. The term "harem" refers to the har hinds in Eq. (12).

$$n \cdot har_v = r\{Por_v \cdot n_h\} \tag{12}$$

The quantity of hinds in the nth harem is denoted as *Nhind*, while the overall quantity is *Nhind*. Through the process of random selection, hinds are allocated to each male commander. Both females and males will construct the nth harem.

Mate harem commander with percent hinds.

In GA, this is represented as a "crossover" model. The parental figures in this context are the male commander and his harem hinds. Their offspring are innovative solutions. The Eq. (13) represents the quantity of harem hinds that engage in mating with their male commander.

$$n \cdot har_v^{mate} = r\{\propto \cdot n \cdot har_v\}$$
(13)

Determine the quantity of female deer in the nth harem that are prepared to engage in mating with the male Red Deer.

The leader of one harem with a percentage of hinds in another.

Randomly choose a harem and allow the male leader to mate with a certain percentage of hinds. A male Red Deer ambushes another harem in order to assert dominance over his territory. The Eq. (14) represents the quantity of hinds that engage in mating with a single male Red Deer within a harem.

$$n \cdot har_v^{mate} = r\{\beta \cdot n \cdot har_v\} \tag{14}$$

Determine the quantity of females in the nth harem who are willing to engage in mating with a single male Red Deer. The selection is likewise made in a random manner.

The nearest hind mate stag.

During this phase, stags engage in mating with their nearest hinds. During the mating season, male Red Deer typically pursue the hind that is most easily accessible, potentially their preferred choice. It is possible that this individual is residing in a harem or frequenting another. Each stag should mate with the hind that is closest to them. In worst-case scenarios, male Red Deer derive advantages from the opportunity to engage in mating with a limited number of hinds, leading to a single mating event. To determine the nearest, it is necessary to compute the distances between each stag and all hinds. The activities exhibit characteristics akin to a 2D approach. The distance in the *J* dimension between a male Red Deer and all hinds is determined using Eq. (15).

$$dim_i = \left(\sum_{j \in J} \left(s_j - h_j^i \right)^2 \right)^{\frac{1}{2}} \tag{15}$$

To enhance further process the Dwarf Mongoose Optimization is used. During the scout group session, if the family travels a considerable distance, they will encounter a suitable sleeping mound. Eq. (16) is used to mimic the scout mongoose.

$$X_{i+1} = \begin{cases} X_i - CF \cdot \pi \cdot \text{rand} \left| X_i - \vec{M} \right|, \text{ if } \varphi_{i+1} > \varphi_i \\ X_i + CF \cdot \pi \cdot \text{rand} \left| X_i - \vec{M} \right|, \text{ otherwise} \end{cases} \tag{16}$$

where, in the range [0, 1], rand is a random value; Eq. (17) determines the *CF* value; and Eq. (18) determines the $\vec{M}$ value.

$$CF = \left(1 - \frac{iter}{M\,ax_{iter}} \right)^{\left(2 \times \frac{iter}{M\,ax_{iter}} \right)} \tag{18}$$

$$\vec{M} = \sum_{i=1}^{n} \frac{X_i \cdot sm_i}{X_i} \tag{19}$$

Babysitters are often subordinate individuals who are responsible for caring for the children and are regularly rotated to allow the dominant female (mother) to lead the rest of the group on daily hunting trips.The feature selection procedure is described in Fig. 4.

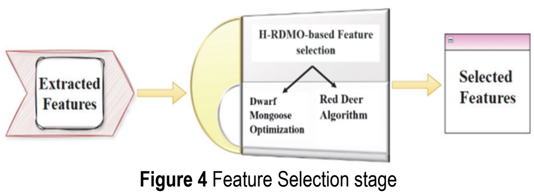

Figure 4 Feature Selection stage

Contributions:

- H-RDMO is probably designed to optimize the choice of functions from the output of the CNN. This optimization ensures that the maximum relevant and discriminative capabilities are chosen for further evaluation and modeling.
- In PA, datasets can be high-dimensional due to the nature of sensor facts or photo inputs. H-RDMO in all probability enables in reducing dimensionality whereas preserving crucial information, leading to greater efficient and effective ways.
- Feature selection is essential in system learning to balance model performance (accuracy, generalization) with computational complexity and useful resource requirements. Probably, H-RDMO aims to achieve this balance by selecting a subset of functions that best describes the data without adding noise or unnecessary redundancy.

3.3 Detection and Classification

PA uses improved methods to detect and classify agricultural occurrences. This involves using Attention-based RNNs for precise detection and Q-Learning and Policy Gradient approaches for accurate agricultural data classification to improve farming decision-making

3.3.1 Detection Using Attention Based RNN

Attention-based totally Recurrent Neural Networks (RNNs) have revolutionized sequential statistics processing across domains like time-series prediction, sentiment evaluation, and machine translation. They succeed by way of specializing in pertinent parts of input sequences, improving mastering and version overall performance significantly. Unlike conventional RNNs, attention-primarily based ones allocate weights dynamically, emphasizing relevant segments based totally on their importance. In PA, information spans soil moisture, temperature, crop health, and weather. Attention-based RNNs adapt to those dynamic datasets, prioritizing essential functions primarily based on context. For example, they will emphasize temperature at some stage in frost events and soil moisture in the course of dry spells. Attention rankings are computed based on function relevance, creating context vectors that manual predictions. Integrating deep reinforcement learning (DRL) similarly complements the version's predictive abilties. By leveraging complicated algorithms and past reviews, DRL refines agricultural strategies over time. Attention-primarily based RNNs and DRL are beneficial gear for obligations like crop yield prediction, disease detection, and aid optimization, making them pivotal in advancing Precision Agriculture's efficiency and effectiveness.

Contributions:

- Processing Data Sequentially: RNNs are ideally suited for tasks where the sequence of the input data is critical, like time series data in agriculture, where historical trends are important, because they are made to handle sequential data.
- Gathering contextual Data: When generating predictions, the RNN's attention mechanism enables the model to concentrate on pertinent segments of the input sequence. It gives varying weights to various segments of the input sequence, prioritizing pertinent data and excluding noisy or unnecessary information.
- Extended Reliance: Understanding trends and patterns in agricultural data over time requires the ability to capture long-term dependencies in sequential data, which RNNs provide.

3.3.2 Classification using Hybrid Q-Learning and Policy Gradient

This section presents the paper's primary contribution, a method for combining policy gradient and Q-learning. Initially, demonstrate the method in a batch update context, assuming perfect knowledge of Q^{φ}, also known as a perfect critic. The technique's practical application in a reinforcement learning situation with function approximation is later covered. Use the policy to define the estimate of Q in Eq. (20)

$$\tilde{Q}^{\varphi}(t,b)=\beta\left(\log\varphi(t,b)+I^{\varphi}(t)\right)+W(t) \tag{20}$$

$$\Delta\theta \propto \underset{t,b}{F} Q^{\varphi}(t,b)+\beta \underset{t}{F}\nabla_{\theta} I^{\varphi}(t) \tag{21}$$

$$\begin{aligned}\tilde{Q}^{\varphi}(t,b)&=\tilde{A}^{\varphi}(t,b)+W(t)=\\&=\left(\log\varphi(t,b)+I^{\varphi}(t)\right)+W^{\varphi}(t)\end{aligned} \tag{22}$$

where, unlike in Eq. (22), W does not always equal W^{φ} and instead has parameters x. Although the constant is frequently computed in practice to be used in a variance reduction strategy, it was not required to estimate it in Eq. (21) because the update was invariant to constant offsets.

$$\begin{aligned}&\Delta\theta \propto \underset{t,b}{F}\left(U\cdot\tilde{Q}^{\varphi}(t,b)-\tilde{Q}^{\varphi}(t,b)\right)+\nabla_{\theta}\log\varphi(t,b),\\&\Delta x \propto \underset{t,b}{F}\left(U\cdot\tilde{Q}^{\varphi}(t,b)\right)\nabla_{x}W(t)\end{aligned} \tag{23}$$

Eq. (23) is an actor-critic method with an optimized (and so biased) critic; it is also Q-learning applied to a specific form of the Q-values. The regularized policy gradient update in Eq. (21) and the Q-learning update in Eq. (23), which are two updates to the policy, are all that makes up the complete method. If the architecture offers an action-value critic Q^{φ}, a value function estimate W, and a policy φ, then the parameter updates can be expressed as (suppressing the (t, b) notation).

$$\begin{aligned}&\Delta\theta \propto (1-\zeta)\underset{t,b}{F}\left(\tilde{Q}^{\varphi}-Q^{\varphi}\right)\nabla_{\theta}\log\varphi+\\&+\zeta\underset{t,b}{F}\left(U\cdot Q^{\varphi}-\tilde{Q}^{\varphi}\right)\nabla_{\theta}\log\varphi\end{aligned} \tag{24}$$

$$\Delta x \propto (1-\zeta) \underset{t,b}{F}\left(Q^{\varphi}-\tilde{Q}^{\varphi}\right)\nabla_x W + \\ +\zeta \underset{t,b}{F}\left(U \cdot Q^{\varphi}-\tilde{Q}^{\varphi}\right)\nabla_{\theta} W \tag{25}$$

Here, the weighting parameter $\zeta \in [0, 1]$ determines the percentage of each update that is applied in Eq. (24) and Eq. (25) respectively. The aforementioned plan reduces to an entropy regularized policy gradient when $\zeta = 0$. It transforms into a (batch) Q-learning variation with an architecture resembling the dueling architecture if $\zeta = 1$. A hybrid between the two is produced by intermediate values of η. The update manner well-known shows a change in the positions of mistake terms. While the second one time period enhances optimality through the years, the primary time period prioritizes consistency with grievances. However, a term lowering errors have to minimally effect the constant issue, given the Bellman residual's likely minimal below a preferred policy gradient. This replace resembles an actor-critic version, wherein the critic is a fusion of a choicest and conventional critic. Combining expected-SARSA and Q-studying, with Q-values as a bonus-characteristic product, gives every other perspective in this replace's dynamics.

Challenges:

- RNNs specialize in studying sequential facts with the aid of greedy temporal dependencies, important for accurate predictions in PA, given the dynamic nature of factors like crop fitness and climate.
- RNNs with the sense mechanism manipulate variable-duration PA statistics, which include sensor time collection, correctly getting to know from the statistics' sequential nature.
- The attention mechanism allows manipulate PA databases by way of specializing in important features, enhancing prediction accuracy while fending off facts overload**.**

3.3 Security-Egret Swarm Optimization with Modified ECC and ElGamal (ESMECC-Elg) Encryption

The encryption and decryption processes typically include both parties. The two parties at the encryption (let's call Alice) and decryption (let's call Bob) ends. Right now, Alice would like to send Bob a secure message. Elliptic Curve Cryptography (ECC) and ElGamal encryption are integrated into the proposed machine to enhance records protection in Precision Agriculture (PA). ECC, recognized for its computational efficiency and strong encryption, is used for key control and encrypting smaller statistics blocks. ElGamal encryption enhances ECC through securing larger data blocks and ensuring confidentiality for the duration of sharing. Public and personal key pairs are generated using ECC, making sure particular encryption and decryption abilties for every player. This hybrid approach ensures secure information transmission, authentication, and integrity verification, vital for maintaining facts security in PA. The ElGamal Elliptic Curve Cryptosystem is implemented in seven steps, each of which is explained below.

System setup: In order to set up an elliptic curve cryptosystem, both parties must decide on the underlying finite field F_p, the elliptic curve coefficients "a" and "b" for a suitable elliptic curve, the generator point G on the curve, the order of G or n, and the cofactor $h = \# E\left(F_p\right)/n$ are all part of the same set of ECC domain parameters.

the same collection of algorithms that are used to represent the points on the elliptic curve and carry out the operations on the elliptic curve in the selected finite field.

Key Generation: The public and private key pair must then be generated by both entities.

The key generation algorithm:

Choose k at random from the interval $[1, n-1]$.

Determine $Q = k \cdot G$. The public key is "Q," and the private key is "k"

Assume Bob has the same private and public key pair (K_b, Q_b) as Alice (K_a, Q_a).

Public Key Validation: The entity receiving the public key of another (let's assume Q) must do the following actions to confirm the legitimacy of the public key.

Verify that $Q \neq 0$, the infinity point.

Verify that $\left(X_Q, Y_Q\right) \in F_p$ where X_Q and Y_Q stand for point Q's X and Y coordinates, respectively.

Verify that Q is located on the elliptic curve that a and b define.

Verify that the point at infinity, $n \cdot Q = 0$, exists.

The IECC encryption technique is predicated on high quantity capabilities to set up a foundation point curve for superior ECC. However, ECC implementation complexity can result in errors and decreased security. Improved ECC generates a mystery key for more potent encryption, enhancing gadget safety and making records identification hard.

The Egret Search Optimization (ESO) method is proposed for secret key encryption, proposing 3 mechanisms: sit-and-wait, competitive approach, and discriminant circumstance. Inspired with the aid of Egret species, ESO employs unique actions like leading ahead (E_1), random walks (E_2), and encircling for balanced exploitation and exploration (E_3), ensuring fast searches in optimization issues. Fig. 6 shows the ESO's Complex Search Behavior

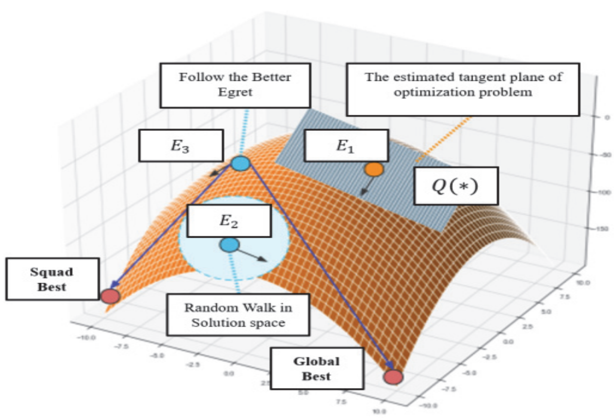

Figure 6 ESO's elaborate search behavior

4 RESULT AND DISCUSSION

The results and a discussion of the suggested model are provided in this section. The hybrid model known as ESMECC-Elg, which combines ElGamal and Modified ECC encryption algorithms with Egret Swarm Optimization, is presented in this work. A number of measures are employed to evaluate the performance efficacy of the suggested technique, including, precision, Matthew's correlation coefficient (MCC), accuracy, False Negative Rate (FNR), sensitivity, F-measure, False Positive Rate (FPR), specificity, and F-measure. The recently developed framework is compared to other models, including Proposed, DLiSA [18], YOLO v3 [17], and LEACH [24], in order to evaluate how significantly its performance has improved. Metrics like energy usage, time complexity, and the efficiency of encryption and decryption are also used in security analysis.

4.1 Overall Performance Analysis: Performance Metrics with Existing Frameworks

In this section, the performance evaluation of various frameworks is presented. Tab. 1 displays a comparative analysis of the presented framework and existing models based on performance metrics.

Table 1 Comparative analysis of performance metrics with existing models

Techniques	Proposed	LEACH [24]	Yolo v3 [17]	DLiSA [18]
Sensitivity	0.97	0.959	0.949	0.942
Specificity	0.994	0.958	0.949	0.947
Accuracy	0.984	0.936	0.927	0.921
Precision	0.97	0.908	0.905	0.9
Recall	0.976	0.917	0.913	0.909
F-Measure	0.969	0.91	0.902	0.898
NPV	0.988	0.941	0.933	0.929
FPR	0.011	0.099	0.102	0.112
FNR	0.042	0.084	0.085	0.092
MCC	0.952	0.872	0.87	0.862

The Tab. 1 offers an assessment of several techniques primarily based on diverse performance metrics. The proposed approach indicates robust overall performance throughout maximum categories as compared to LEACH, Yolo v3, and DLiSA. Specifically, the proposed technique demonstrates better Sensitivity (0.97), Specificity (0.994), Accuracy (0.984), Precision (0.97), Recall (0.976), F-Measure (0.969), NPV (0.988), and MCC (0.952) values as compared to the other techniques. It also exhibits a lower False Positive Rate (FPR) of 0.011, indicating better avoidance of misclassifying negatives as positives. These results advocate that the proposed method plays well across more than a few evaluation standards and is specifically effective in efficaciously figuring out each wonderful and terrible instance, attaining excessive accuracy and reliability in classification tasks.

4.2 Overall Performance Analysis: for Security

In this section, metrics such as energy usage, time complexity, and the efficiency of encryption and decryption are utilized for security analysis. Tab. 2 presents a comparative analysis of the presented framework and existing models based on these security analysis metrics.

The Tab. 2 gives a comparative evaluation of 3 encryption techniques: ESMECC-Elg, ECC, and ElGamal, across various performance metrics. The well-known ESMECC-Elg shows superior performance in phrases of electricity intake, with the lowest of 150 J in comparison to ECC at 187 J and ElGamal at 203 J. It additionally displays quicker encryption and decryption times, with values of 1.18 s and 0.0091 s, respectively, outperforming ECC (2.54 sencryption, 0.012 s decryption) and ElGamal (3.87 s encryption, 0.034 s decryption). Additionally, ESMECC-Elg demonstrates a decrease time complexity of 3.6 s, indicating a more green computational process in comparison to ECC (4.7 s) and ElGamal (4.2 s). These effects together highlight ESMECC-Elg's performance and effectiveness as an encryption technique, making it a promising desire for stable facts transmission and protection.

Table 2 Performance analysis based on the security analysis metrics

Techniques	ESMECC-Elg	ECC	ElGamal
Energy Consumption / J	150	187	203
Encryption / s	1.18	2.54	3.87
Decryption / s	0.0091	0.012	0.034
Time Complexity / s	3.6	4.7	4.2

Limitations:

- Traditional PA records exchange lacks protections, risking facts privacy and unlawful get right of entry to mainly sensitive statistics susceptible to cyber-assaults.
- Disparate records get entry to among stakeholders hinders comprehensive evaluation and collaboration, creating data storage tower and restricting seamless interchange.
- Unclear facts sharing strategies and possession worries may delay association, leading to inefficiencies and reluctance to percentage essential agricultural insights.

5 CONCLUSIONS

PA needed a smart and safe foundation, therefore blockchain and IoT were incorporated. Blockchain and deep reinforcement learning could be used to secure PA data exchange. The major purpose was to use blockchain to securely share PA data. IoT devices initially collected data on essential aspects including weather, temperature, humidity, crop health, and soil moisture. Data was preprocessed using z-score and Decimal Scaling standardization. Data was evaluated and clustered using BIRCH after pre-processing. It was scalable and successful for large dataset clustering. Extracting features with CNN, known for their independent feature learning and resilient computation, improved accuracy and automation. H-RDMO selected the best characteristics after feature extraction. Sequential data was accurately predicted using an Attention-based RNN. A Hybrid Deep Reinforcement Learning technique using a policy gradient model and hybrid deep Q-learning classified illnesses accurately. Finally, Hybrid Modified ECC with ElGamal encryption protected data during sharing. PYTHON is used to apply the suggested model, which is evaluated using accuracy, precision, recall, F-score, specificity, sensitivity, MCC, NPV, FPR, and FNR. Optimized H-RDMO yields 98.4% accuracy and 97% precision compared to current approaches, whereas ESMECC-Elg consumes 150 J.

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