LightAgro: Lightweight Blockchain IoT Based Fabrication for Smart Irrigation

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Abstract

India is supposed to be the global agricultural powerhouse. Around three-quarters of Indian family rely on agriculture for their livelihood. Water is the most crucial resource that must be accounted for to create a better irrigation system. The introduction of IIoT 4.0 also expanded its contribution to smart irrigation (SI). IoT-based innovative irrigation management achieves optimum water-resource utilization, bridging the gap between cyber-physical Systems (CPS). This paper improves the prediction rate needed for irrigation by sensing different parameters like temperature, pH value, humidity, NPK fertilizer, and rainfall of the crop field. In this paper, Deep Learning, an AI-based proposed system, integrates remote sensor data to predict irrigation in intelligent agriculture correctly. As open-source technology is involved in decision-making, security and trust issues are at stake. We propose a shallow neural network model, namely, LightAgro autonomous network, to recover intruder issues. LightAgro outputs (local prediction) are securely

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signed using a lightweight secp256k1 curve for users' authentication. The vast amount of sensor data stored in client-server architecture in traditional systems is challenging. The result shows ML accuracy of 85.26 % using Gradient boosting techniques.

Keywords: SF, SI, LightAgro, ML, SC, Blockchain.

1 Introduction

According to a 2024 UN World Water Development Report, the agricultural share of freshwater demands 70 % of the world's freshwater, much higher than industrial needs. According to the demographic report, estimation shows that by 2050, India's population will reach a surplus of up to 1.69 billion. But current food availability is not sufficient as per the need. To make India a self-resilient nation, we should focus on the agricultural sector by maximizing production and minimizing resource utilization using advanced technologies. SI is an emerging phenomenon that alludes to overseeing data integrity and communication in ranches to extend the advancement requirement in human work and retain good quality crop production. In [14], D Vallejo-Gomez et al. proposed a literature review on innovative irrigation systems. A modified PRISMA 2020 method analyzes detailed analytical phrases on this topic. Automation in rural and urban agriculture is the prior most interest of the researchers. In [17], M Gupta et al. suggested a multi-layer architecture in the precision agriculture sector. This paper has mainly focused on the different distributed cyber-physical environments. It highlights the cyber-attack scenario broadly and also focuses on open research challenges. In [18], authors proposed an innovative farming technique to enhance information communication technology. They have introduced big data to deal with a large volume of information related to socio-economic challenges. This paper gives an insight into the food supply chain network to overcome governance issues in business models. In [20], Mohy-iodine et al. focused mainly on network instruction systems to reduce vulnerabilities in the smart agricultural field. Various ML techniques, such as XGBoost (XGB) and AdaBoost (ADA), are used to find model accuracy and detect anomalies. The Matthews-correlation coefficient (MCC) gives 96.92% accuracy in overcoming NF-Bot-IoT lopsidedness. In [21], Cordeiro et al. announced a fog-enabled intelligent irrigation system using a deep neural network to meet agricultural needs. Optimizing the use of water is the primary concern of this paper. The fog computing system resolves the connectivity problem in the farm area. The performance metrics show predictions based on CPU and RAM usage. The maximum consumption increases by 10% CPU and 1% RAM.

1.1 Research Contribution

Effective water management is the primary impacting factor of irrigation to assist SF. The primary objectives of SI for SF are labor minimization, timely monitoring, and other resources to maximize efficiency and accuracy. Hence, the contribution of the paper –

1. We proposed a three-layer architecture of the LightAgro framework. The first layer promotes the data collection layer from IoT devices and sensors, followed by the edge and lightweight blockchain layers. The last layer signifies the SC for the authentication of users and the global blockchain layer.
2. Evaluate the ANN-based model incorporated with remote sensor data for the correct prediction of irrigation.
3. We suggested an IoT-Blockchain-based distributed, secured system to assist SF.
4. The predicted results are stored in the local blockchain only after authentication of the user encrypted using the Elliptical curve Digital Signature (ECDSA) algorithm sec256k1 curve is mentioned.
5. The multi-objective proposed system's performance evaluation is observed with constraints on model accuracy, latency, execution time, and gas consumption.

1.2 Construction of this Article

The rest of the paper is as follows: Section 2 presents the related work of different research papers. Section 3 explains the proposed architecture of the work. Section 4 explains the workflow of the proposed system. The result and performance analysis are discussed in Section 5. The last section describes the conclusion and, finally, the references.

2 Related Works

Till now, several ML-IoT-based projects and research have been carried out on agricultural systems. In [2], Sitharthan R et al. explained AI and 6G-enabled smart agricultural irrigation system models based on a prediction algorithm based on rainfall patterns and tremendous climatic changes. Based on the weather history and traces of soil moisture, it is possible to predict with 86.34% accuracy.

In [3], Md. Mamun Hossain et al. presented a review of research on the development of distance monitoring to control irrigation management. The machine learning model helps to decide on water control and fertilizer utilization recommendations. Blockchain has been introduced to ensure data integrity, man-in-the-middle MITM attacks, and denial of service (DDOS)attacks.

In [5], the authors describe a case study of water storage solution techniques for agricultural production. Ethiopia is mainly a rainfall-shortage country, so water conservation is the utmost priority for cultivation. This paper describes an MVP model to enhance water storage capacity in the agricultural field.

In [6], Asif Irshad Khan et al. show novel SI energy management to promote IoT-enabled SF. The proposed Emperor Penguin Jellyfish Optimizer (EPJO) method shows energy optimization in latency, throughput, and cluster selection compared to traditional methods.

In [7], Nestor Michael Tiglao et al. introduced a novel wireless mesh-based Agrinex system. This system is handy for large-scale farming. It vacillates sensor node reorganizations if any changes are noted in the network. Drip irrigation is feasible in terms of water conservation at a large scale.

In [4, 9], Various weather forecast parameters like temperature, humidity, and precipitation are monitored and collected over cloud-based web services – analysis of forecast data using ML techniques to improve smart irrigation systems.

In [10], A case study of strawberry plants cultivated in a greenhouse cloud-based approach for smart irrigation is mentioned using edge computing.

In [12], Pius Agbulu, G. et al. suggested a water management system LoRa-based smart irrigation control using a hybrid classifier CNN-SVM. The experiments are covered in real-time fields for routine irrigation systems. The solution assured experimental analysis regarding precision, recall, accuracy, and energy efficiency.

In [15], Nawandar et al. proposed a neural network system to monitor irrigation requirements from a distant location based on the current crop situation. It makes the system low-cost and portable.

In [16], Laura and Parra et al. explained a smart farming technique using IoT and WSN technologies to assist intelligent systems. This paper aims to describe the most useful nodes using wireless sensor networks to determine weather conditions and initiate irrigation.

3 Proposed Architecture

Our LightAgro smart irrigation system architecture is described below in Figure 1. It is divided in three Parts-Data Collection Layer, Edge Layer and local Blockchain Formation and lastly Smart Contract Based Management Layer.

3.1 Data Collection Layer

We have implanted sensors connected to routers (R1, R2…Rn) in this first layer. It collects suitable data from the environment and transmits it over

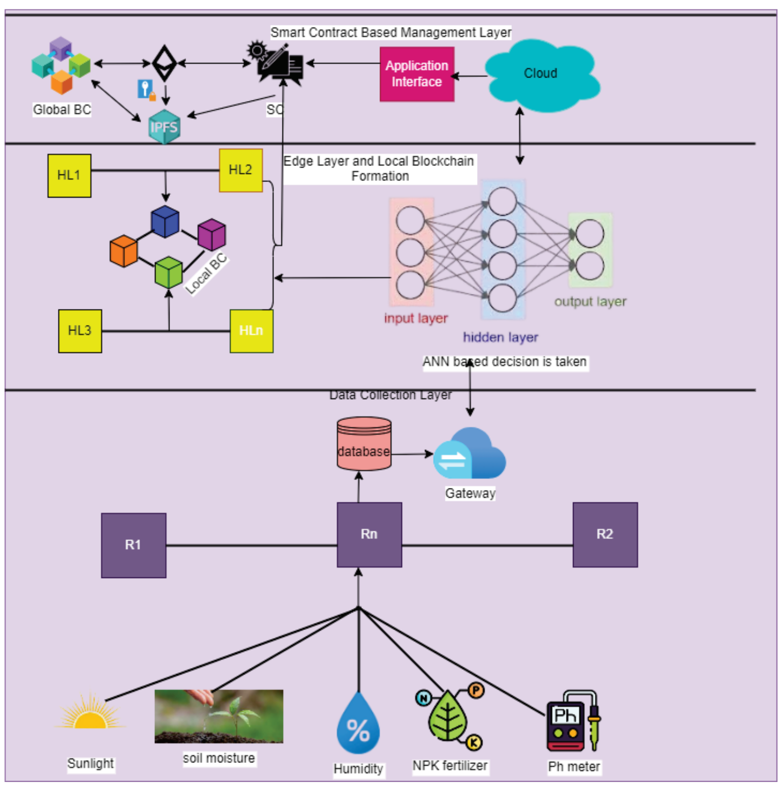


Figure 1 Proposed architecture of LightAgro.

the network. It is more of an interconnected embedded system that helps to determine decisions in an agricultural management system accurately.

1. Our proposed system consists of various sensors, namely soil moisture (VH-400) sensor, humidity sensor (DHT-11), NPK fertilize Sensor (RS485), pH meter, and ample amount of sunlight, all of which are observed and connected to the Arduino Uno Board. Now, these k sensors, including both irrigation sensors, k1, and ambient irrigation sensor (AIS), k2, are mapped to n users effectively with a trivial condition, k = k1+k2. A mapping of En k is quintessential to achieve SI for SF. Where En represents the entity of n users, and k represents the total number of sensors.
2. To establish communication with the edge network, routers (R1, R2. . . Rn) are connected to the Universal Asynchronous Receiver-Transmitter (UART) protocol via the representational state transfer (REST) method. It stores and sends data to the next layer for analyzing and visualizing appropriate data.
3. The desired amount of soil moisture (Threshold value −60%) and NPK fertilizer (Threshold value, 50–75%) based on crop variety controller sets the pump “ON” or “OFF.” It is monitored continuously to check whether irrigation is needed or not. Here, we have considered a sprinkler irrigation system.

3.2 Edge Layer and Local Blockchain Formation

This edge layer is divided into three parts. Firstly, selecting the dataset features sensor data (sunlight, moisture, pH value, NPK fertilizer, humidity) available online. Unwanted NaN values are discarded at the time of feature selection. Secondly, preprocess data with the favorable conditions of irrigation factors –

1. **Sunlight –** The ample amount of sunlight must vary from 50-75F. The variety of seasonal crops will vary. The proper amount of temperature is the most influential parameter for seed germination and nurturing plant growth.
2. **Soil Moisture –** Irrigation primarily depends on soil moisture. If the soil moisture threshold value is below 60%, immediate irrigation must be initialized. It provides moisture present over the crop plane for the growth of plants.
3. **Humidity –** During breathing, plants lose moisture in the dry air. Hence, it is the utmost important factor for watering plants. Depending upon

crop season (e.g., mid summer), humidity is lowest. Generally, 50–60% of the humidity is aquainted.

4. **NPK fertilizer –** With a lack of soil nutrients in plants germination process may be hampered. The ideal ratio of NPK is 4:2:1. This improves macro-level monitoring of soil directly affecting irrigation.
5. **pH value –** As for the growth of plants, fertilizer is used in farms; it varies pH levels present in the soil. For best-case crop growth, pH ranges between 5.5 to 6.5.

With the help of ANN, the AIS features act as the input layer for irrigation. Metadata in the hidden layer take correct decisions using an ensemble classifier (Random Forest, bagging, Gradient Boosting) and gives the best result. This result is conveyed to the cloud and fed to the local blockchain formation.

In the Local Blockchain, the result of significant features of the hidden layer (HL1, HL2, HLn) gives rise to the lightweight Blockchain of our proposed LightAgro system. It significantly works with the user authentication (uses Lightweight elliptical curve sec256k1) for signing and verification purposes. It is previously instantiated to get access control via smart contract (SC).

3.3 Smart Contract-based Management Layer

At this level, data is stored in a heavily weighted Cloud. The user (farmer, admin) controls the application interface, allows AIS as input through ANN, and generates insight (using a pseudo-random generator) over AIS activities. The predicted result via application interface to initiate irrigation *Iirr*. Provides cloud results along with local BC for the execution of rule-based SC. It ensures authorization norms of the National Mission for Sustainable Agriculture (NMSA) and General Data Protection Regulation (GDPR) standard guidelines. For peer-to-peer communication, IPFS is used, containing a key hash of *ck* requires 32 bytes. Subsequently, the result is stored in the Global Blockchain.

4 LightAgro: Dataflow of the Framework

Improving plant health and optimizing water usage, making irrigation systems faster and better. The flowchart of our proposed system is described in Figure 2. It includes remote control and monitoring capabilities, helping farmers from overwatering or under watering the plants. The end device

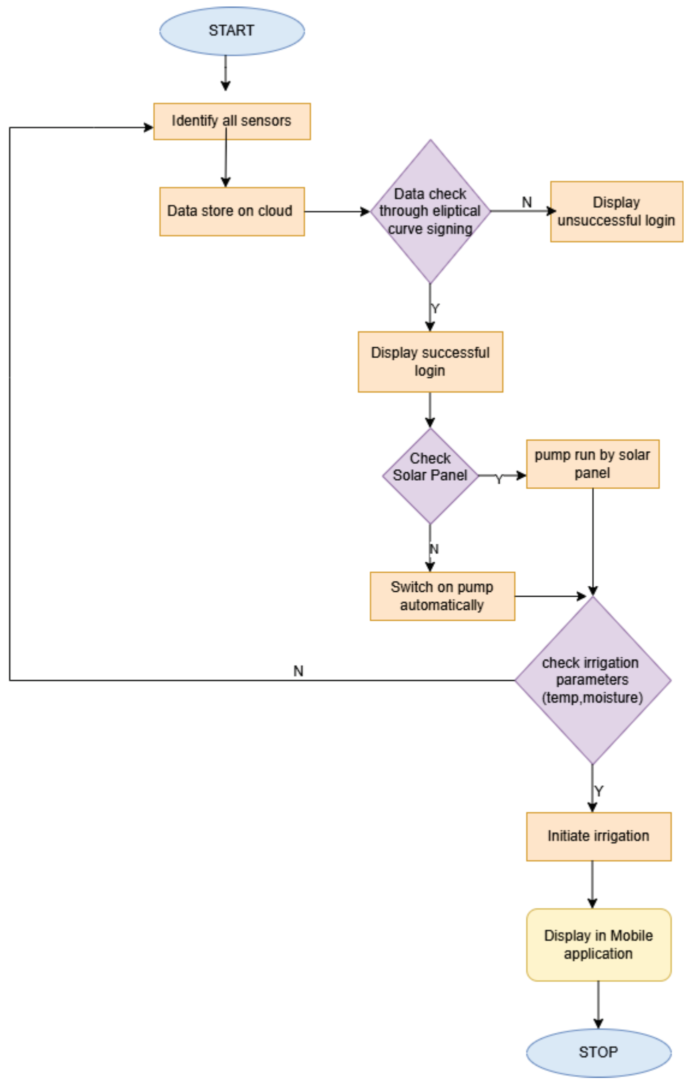


Figure 2 Workflow of LightAgro.

node consists of Arduino UNO, 6G, motor, soil moisture sensor, JXCT soil NPK sensor, temperature sensor, and humidity sensor. The list of devices applicable for smart irrigation is listed in Table 1. The micro-controller device is used as the coordinator device in the network system. An interface Module like MAX485 needs to connect the sensor to the microcontroller. Data can be

Table 1 Apparatus table

Sl. No	Device Name	Function
1	Arduino UNO	Used as a microcontroller
2	MAX485	Interface of Arduino
3	Temperature Sensor	For sensing temperature
4	DHT-11	For sensing humidity in the soil
5	VH-400	For sensing moisture in the soil

viewed on the Android mobile after receiving from the server. Blockchain is introduced in our proposed system to ensure data tampering and forgery. As blockchain nodes are too small, using them in lightweight calculations over DES and AES is beneficial. Blockchain refers to a distributed ledger system where data are stored in blocks connected through a hash function having a unique ID by maintaining the integrity of the blocks. The previous block's hash is attached to the next block along with its data. If any intruder wants to tamper or alter the block data, all the consecutive block hash will be affected. Therefore, any intruder attempts to change the data or spoof any particular block of the Blockchain will not be possible. The web service is written in Blockchain with a lightweight REST API to convey the information between the field gadget and the sensors.

4.1 Algorithm 1: Sign-in Verification Using Lightweight sec256k1 Elliptical Curve

Algorithm 1 describes the authentication of lightweight sec256k1 elliptical curve signing and verification of the user. After the initial setup of a smart contract is built it will check whether the farmer requesting to monitor his land is registered or not in the system. The validators in the local BC do the signing process, which is explained as follows:

$$\mu_i = \mathrm{Sign}(Z_i, K_{pri}) \tag{1}$$

Where μ_i is the authenticated digital signature of the *ith* local prediction is Z_i, and Kpri is the farmer's private key. It is assumed that n signed prediction is mined over $S = \mu_1, \mu_2, \ldots \mu_n$. We have considered the standard hashing function H(...). The hash output are represented as *Hs* = H(S1), H(S2),... H(Sn). At IPFS this data is stored as a reference. The curve order is n, a prime number that presents several points in the curve. The curve has a base point B as the starting point of the curve functionality.

Algorithm 1 Lightweight sec256K1 verified Curve Signing

1: **Input:** Range [1, n − 1]
2: **Output:** n is the order of the sec256K1 curve ensuring the correct signing.

3: **Process:**
4: Sign (Z_i, K_{pri})
5: r ← random value in the range [1, n − 1]
6: Compute P = r · B, where B is the base point of the lightweight curve.
7: Extract the x-coordinate of the point P and denote it as d
8: Find r mod n and denote it as r^{-1}
9: Compute the message digest of the prediction Z_i and denote it as $H(Z_i)$ ▷ Generate the hash of the input data (message digest).
10: Compute the second component of the verifying signature:
$$S = r^{-1} \cdot (H(Z_i) + d \cdot K_{pri}) \bmod n$$
11: **return** signature (d, S)
12: **Verify:** (Z_i, μ_i, K_{pub})
13: Compute the message digest of the prediction Z_i and denote it as $H(Z_i)$
14: Calculate the inverse of S modulo n and denote it as S^{-1}
15: Compute the first component of the signature, denoted as S_1:
$$S_1 = H(Z_i) \cdot S^{-1} \bmod n$$
16: Compute the second component of the signature, denoted as S_2:
$$S_2 = d \cdot S^{-1} \bmod n$$
17: Calculate the elliptic curve point C = $S_1 \cdot B + S_2 \cdot K_{pub}$
18: **If** the x-coordinate of C = d **then**
19: **return** signature is valid
20: **Else**
21: **return** signature is invalid
22: **End if**
23: **End process**

4.2 Algorithm 2: LightAgro-Evapotranspiration Generate Rate of Irrigation

Algorithm 2 describes the calculation of evapotranspiration required for irrigation in the crop field. Potential crop evapotranspiration (E_{Tc}) varies from actual crop evapotranspiration (E_{Ta}) based on soil nutrient, and water level in the ground. The potential crop evapotranspiration follows standard conditions as below:

$$E_{Tc} = K \cdot E_{Ta} \tag{2}$$

Algorithm 2 Impact of evapotranspiration on irrigation

1. **Input:** Evapotranspiration of the crop field.
2. **Output:** How evapotranspiration affects irrigation.
3. **Process Begin**

Algorithm 2 Continued

4. Calculate potential crop evapotranspiration (E_{Tc}) from the water level of the root of the plant.
5. Calculate actual crop evapotranspiration (E_{Ta}) from the water level of the ground.
6. The reduction in E_{Ta} is estimated by irrigation needed to maintain daily water balance:
$$E_{Ta} = K_{ori} \cdot ET_{refer}$$
Where $\mathrm{K_{ori}}$ is the crop coefficient that measures the difference between evapotranspiration of the crop and reference water level.
7. Compute stress coefficient, K_S, that affects Kori estimated as:
$$K_s = \frac{ASW - C_r}{\mathrm{ASW - WAR}}$$
ASW = Available soil water [mm],
   - C_r = Consumption of water in the root zone,
   - WAR = Water available readily for irrigation [mm].
8. The degree of stress coefficient K_S is calculated and termed as D_s.
9. If $\mathrm{D}_s \leq$ WAR, then $\mathrm{K}_S = 1$. The degree of stress is presumed to be fine, and no irrigation is needed.
10. Else
11. Irrigation State: Revert and check again all conditions.
12. **End if**
13. **End**

5 Result and Performance Analysis

5.1 Dataset Description

This dataset is taken from an open-source Kaggle platform. The dataset contains weather condition data about rainfall, humidity, and temperature. Data about soil quality and the nitrogen, phosphorus, and potassium ratio in the soil. Soil's pH is also collected to calculate the evapotranspiration of plants. For training and testing purposes, a different ML model is used. 70% of the data undergo training and 30% for testing. All these data are scaled by standard scalar imported from sklearn.

5.2 Data Analysis

Before execution, any ML classification and estimate data needs to be preprocessed. A correlation heatmap is used to observe the correlation matrix between variables in the dataset. The results of the analyzed data are shown in the Figures 3–7. This correlation heatmap is expressed in Equation (3).

$$Corr(A, B) = \frac{cov(A, B)}{\sigma_a \sigma_b} \tag{3}$$

Here, cov is the covariance, and σ_a, and σ_b are the standard deviation of A and B respectively.

In the correlation heatmap, a score close to 1 determines a strong relationship whereas a score close to 0 determines a weak relationship respectively.

5.3 Performance Measurement of ML Models

The accuracy of different models is calculated and verified based on precision, recall, and F1-score. The mathematical formulation of the measurement metric is as follows –

Precision calculates the classifier differential rate and correctly predicted observations to all expected true positive observations in Equation (4).

$$Precission = \frac{\textit{True Positive}(TP)}{\text{True Positive(TP)} + \text{False Positive(FP)}} \tag{4}$$

Recall calculates the number of correctly predictive true positive observations for all actual class observations in every classifier in Equation (5).

$$Recall = \frac{\textit{True Positive}(TP)}{\text{True Positive(TP)} + \text{False Positive(FP)}} \tag{5}$$

F1 score measures the overall accuracy combining precision and recall in Equation (6).

The more the F1 score means it has a smaller number of FP and FN.

$$F1\ score = \frac{2X\ Precission\ X\ Recall}{Precision + Recall} \tag{6}$$

$$Accuracy = \frac{TP + FN}{TP + FP + FN + TN} \tag{7}$$

For the calculation of the accuracy of the total samples, Equation (7) is used. It indicates how a model is trained successfully and predicted correctly.

5.4 Data Normalization

To achieve accuracy, all data has to be normalized to discard missing values in the dataset's feature selection. Different processing layers produce the final output by linear convolutions of inputs. The ReLU activation function transforms the input data nonlinearly. Activating a layer after individual convolution involves batch normalization.

5.5 Hidden Layer Calculation

The input of all hidden neuron HL1...HLn is calculated as a weighted sum of inputs $(w_i i_n)$ plus a bias(b).

$$Y(\mathrm{HL}_1) = (w_1 i_1 + w_2 i_2 + \cdots w_i i_n + \mathrm{b}) \tag{8}$$

The ReLU function is defined as

$$\psi(x) = max(0, \mathrm{x}) \tag{9}$$

The range of ReLU activation function $\psi(x)$ is taken between 0 to x.

$$\mathrm{Output} = \psi(\mathrm{w_1 i_1 + w_2 i_2} + b) \tag{10}$$

The value of the output is updated after each convolution in the hidden layer.

In Figure 8 it has been observed how different parameters of irrigation effect on crop production widely. Figure 9 compares the energy consumption over water management [6, 7].

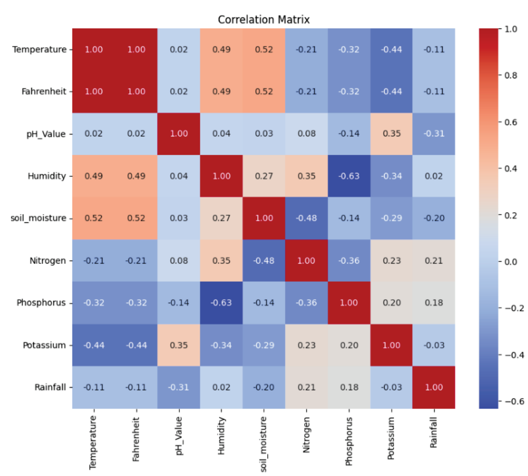


Figure 3 Co-relation matrix of different data features of the dataset.

```
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
GradientBoosting Accuracy: 50.00%
GradientBoosting Latency: 4.8350 seconds
GradientBoosting Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00         3
           1       1.00      1.00      1.00         5
           2       0.00      0.00      0.00         0
           3       0.00      0.00      0.00         4
           4       0.25      0.67      0.36         3
           5       1.00      0.33      0.50         3
           6       0.50      1.00      0.67         2
           7       1.00      0.50      0.67         4
           8       1.00      0.50      0.67         2
           9       1.00      0.33      0.50         3
          10       0.25      1.00      0.40         1

    accuracy                           0.50        30
   macro avg       0.55      0.48      0.43        30
weighted avg       0.63      0.50      0.49        30

RandomForest Throughput: 1.1466 accuracy/sec
Bagging Throughput: 0.7677 accuracy/sec
GradientBoosting Throughput: 0.1034 accuracy/sec
```

Figure 4 Comparison over ML models.

```
RandomForest Accuracy: 56.67%
RandomForest Latency: 0.1497 seconds
RandomForest Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00         3
           1       1.00      1.00      1.00         5
           2       0.00      0.00      0.00         0
           3       0.00      0.00      0.00         4
           4       0.29      0.67      0.40         3
           5       1.00      0.33      0.50         3
           6       1.00      1.00      1.00         2
           7       1.00      1.00      1.00         4
           8       1.00      0.50      0.67         2
           9       1.00      0.33      0.50         3
          10       0.33      1.00      0.50         1

    accuracy                           0.57        30
   macro avg       0.60      0.53      0.51        30
weighted avg       0.67      0.57      0.57        30
```

Figure 5 Accuracy calculation over random forest ML technique.

```
Epoch 37/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8883 - loss: 0.2419 - val_accuracy: 0.8526 - val_loss: 0
Epoch 38/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8784 - loss: 0.2428 - val_accuracy: 0.8632 - val_loss: 0
Epoch 39/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8809 - loss: 0.2369 - val_accuracy: 0.8842 - val_loss: 0
Epoch 40/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8879 - loss: 0.2275 - val_accuracy: 0.8421 - val_loss: 0
Epoch 41/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8789 - loss: 0.2667 - val_accuracy: 0.8632 - val_loss: 0
Epoch 42/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8816 - loss: 0.2440 - val_accuracy: 0.8526 - val_loss: 0
Epoch 43/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8818 - loss: 0.2518 - val_accuracy: 0.8632 - val_loss: 0
Epoch 44/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8658 - loss: 0.2645 - val_accuracy: 0.8526 - val_loss: 0
Epoch 45/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8796 - loss: 0.2413 - val_accuracy: 0.8737 - val_loss: 0
Epoch 46/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8748 - loss: 0.2365 - val_accuracy: 0.8526 - val_loss: 0
Epoch 47/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8972 - loss: 0.2224 - val_accuracy: 0.8632 - val_loss: 0
Epoch 48/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8763 - loss: 0.2403 - val_accuracy: 0.8632 - val_loss: 0
Epoch 49/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8663 - loss: 0.2582 - val_accuracy: 0.8421 - val_loss: 0
Epoch 50/50
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - accuracy: 0.8966 - loss: 0.2467 - val_accuracy: 0.8526 - val_loss:
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8667 - loss: 0.3030

Model Accuracy: 85.29%
Model Loss: 0.3086
```

Figure 6 Accuracy calculation over gradient boosting.

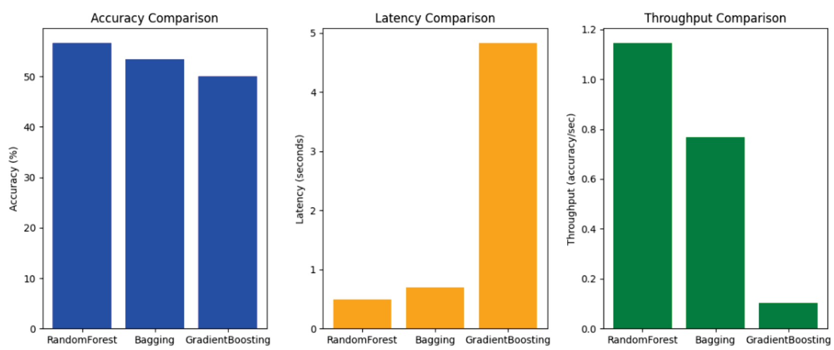


Figure 7 Comparison of different ML models.

5.6 LightAgro Model Performance in Blockchain Layer

- **Prevention against unauthorized access:** Any anonymous attacker may try to modify or insert data to hamper the system's performance. Blockchain protects against such attacks through hash value checking every time for authentication. It is capable of identifying any alteration made over the network chain.

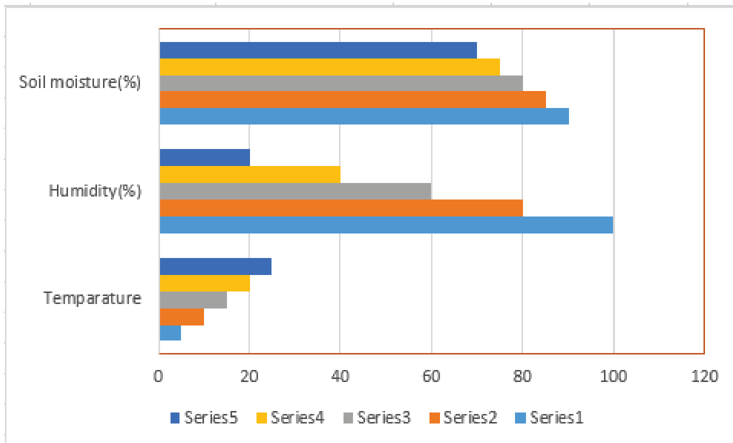


Figure 8 Variation over different parameters of irrigation.

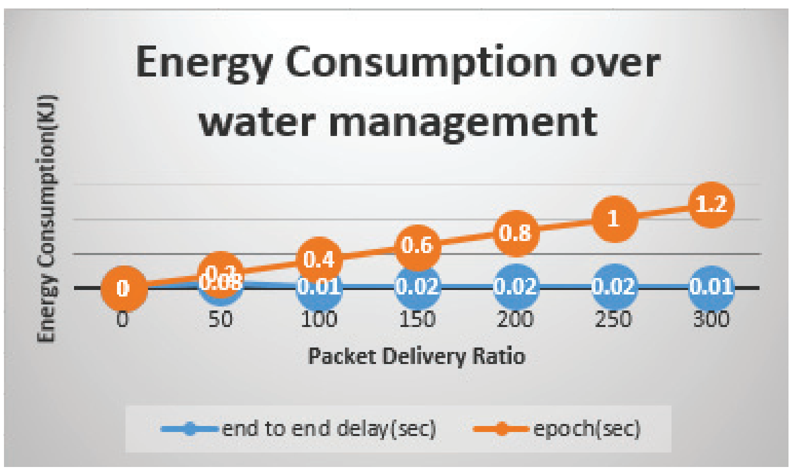


Figure 9 Variation over different parameters of irrigation.

- **Prevention from data duplicity and data loss:** Decentralization is a notable feature of Blockchain. As data is not stored only at a single point location, it reduces the possibility of data loss in the network. Moreover, keeping information of data in distributed form removes data duplicity problems in the system.
- **Prevention from DoS attack:** The denial-of-service attack may include user log in details and parameter details of the irrigation process, leading to a slowdown of the services. Trespassers may try to stop transactions

under a DoS attack. So, to prevent Blockchain, the network must operate in a fixed time frame.

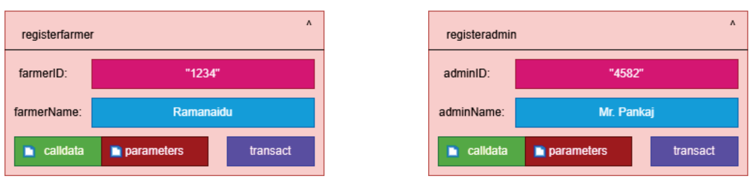
5.7 Permission-based Smart Contract

This subsection uses the permission-based smart contract to generate access control over the network. Data is fetched from local BC and IPFS to perform SC. For this purpose, we have used different functions to authorize entry into the Blockchain network. A mapping function is helpful to map the details of other parameters to view the functionalities of the parameters.

Figure 10(a) represents the farmer registration. Similarly, Figure 10(b) represents the admin registration satisfying only authenticated admin is invoked. Both of the records of registration of user will be store in the global blockchain.

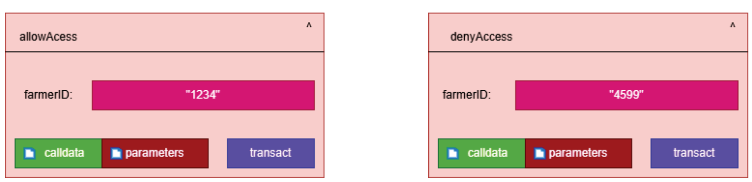
Figure 11(a) shows if the user login matches it will allow user to enter in the LigtAgro system. Figure 11(b) shows that if the data is not found in cloud access is denied immediately.

The Mapaccess function is invoked to check the need for irrigation in crops. Figure 12(a) authorizes and limits the admin to view the particular farmer details. Finally, Figure 12(b) shows the details of parameters of the hashed farmer details.



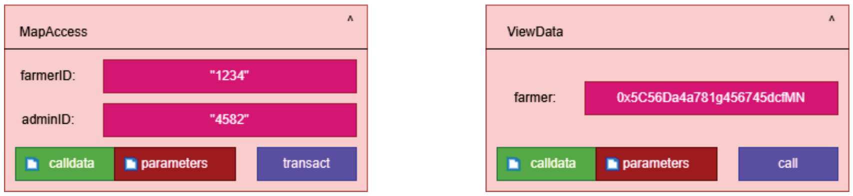
(a) Registration of the farmer (b) Registration of the admin

Figure 10 Registration process.



(a) Allow access to the user (b) Deny access to the user

Figure 11 Authentication for access.



(a) Revoke access (b) View access of the record

Figure 12 Mapping.

6 Conclusion

We have tried to resolve farmers' most common challenges to enhance productivity. With the integration of IoT, machine learning (ML), and blockchain, profitability is maximized in crop production. Calculating the evapotranspiration of plants helps initiate irrigation. As it depends on the leaf area of plants and the ground-level water absorbed by the root, it helps to monitor plant health promptly. The user-friendly application recommendation for NPK fertilizer usage gives an insightful approach to crop production. Less expenses and higher productivity enrich agricultural management through our LigtAgro proposed System. Introducing blockchain technology improves trust and makes for higher throughput. Trusted devices achieve data transparency and integrity when they participate in the network. Evapotranspiration attains the water consumption, making the environment sustainable. Remote monitoring of crop fields automatically makes the System more effective and promising. We have applied a random forest ML model to achieve 85.29 % accuracy.

Furthermore, the suggested framework enhances information exchange. Over- or under-irrigation systems may give birth to several plant diseases that degrade landscape conditions. Wastewater management is a boon in drought-prone areas to maximize agricultural growth. Solar energy harvesting increases the battery life of motors, leading to a green environment. Researchers can explore the interoperability of parameters in the farm sector through further research and enhancement. Technological achievement with a larger area of device connectivity in real-time will make it more efficient and robust and create an eco-friendly environment.

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Priya Saha received the bachelor's degree in Information Technology from Maulana Abul Kalam Azad University (MAKAUT), West Bengal in 2011, the master's degree in Computer Science & Engineering from Maulana Abul Kalam Azad University (MAKAUT), West Bengal in 2015, and pursuing philosophy of doctorate degree in Computer Science & Engineering from National Institute of Technology Patna (NITP), respectively. She is currently working as an Assistant Professor at the Department of Computer Science & Engineering, Sikha 'O' Anusandhan (Deemed To Be) University. Her research areas include Blockchain, Deep Learning, IoT and Machine Learning.

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