Optimized Fertilizer Dispensing for Sustainable Agriculture Through Secured IoT-Blockchain Framework

IoT-Blockchain Framework for Sustainable Agriculture

B. C. Preethi[1]*, G. Sugitha[2], T. B. Sivakumar[3]

Department of Electronics and Communication Engineering, St.Xavier's Catholic College of Engineering, Nagercoil, India[1]
Department of Computer Science and Engineering, Muthayammal Engineering College (Autonomous), Rasipuram, India[2]
Department of Computer Science and Engineering-Vel Tech Rangarajan,
Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India[3]

***Abstract*—Precision farming is essential for optimizing resource use and improving crop yields to attain sustainable agriculture. However, challenges like data insecurity, fertilizer costs, and inadequate consideration of soil health pose a hindrance to achieving these goals. To overcome these issues, the proposed work presents a novel approach for optimizing fertilizer dispensing by developing a framework connecting IoT and blockchain with a community of greenhouses. The system consists of IoT sensors installed inside the greenhouses to measure soil pH and nutrient values. This collected sensor data is compressed and stored securely and in an off-chain manner by the IPFS (Inter-Planetary File System) hash using the Keccak-256. MetaMask transfers the data for blockchain registration and authentication. The data is then preprocessed using Z-score normalization, Label Encoding, and One-Hot Encoding to obtain a precise analysis. A Deep Learning-based Convolutional Neural Network (DL-CNN) is used to classify soil conditions and determine the appropriate fertilizer requirements. The results of the DL-CNN model are viewed in a dashboard through a Decentralized Application (D-App) that we developed to provide real-time information to consumers, field analysts, and agricultural organizations. Field analysts use the information to establish a control center for precisely applying fertilizers. The proposed method achieves a classification accuracy rate of 98.86%, thus increasing soil health and providing a solution for effectively managing fertilizers.**

Keywords*—Fertilizer dispensing; IoT sensors; blockchain; deep learning; convolutional neural network; greenhouse management; and decentralized application

I. Introduction

Smart agriculture, also known as smart farming, focuses on using advanced technologies and data-driven operations to improve sustainability in agricultural production [1]. In this area, IoT-enabled sensors are used to monitor some parameters in real-time and provide cutting-edge management of farming data [2]. The use of blockchain technology in the field of smart agriculture guarantees security, transparency, and tamper-proof data storage, as well as the maintenance of trust and provenance along the agricultural chain [3]. Moreover, blockchain in smart agriculture securely transfers and stores data to decide soil health and fertilizer applications [4, 5]. This method optimizes resources, increases crop yields, minimizes environmental impact, and enhances food safety by offering verifiable data to consumers [6]. Blockchain and IoT agriculture improve decision-making and the ability to implement decentralized solutions that help farmers and provide better outcomes [7].

Previous research in smart agriculture has mostly addressed the application of IoT sensors that monitor environmental conditions to improve crop management [8, 9]. The techniques of machine learning (ML), deep learning (DL), and cloud computing have been applied for processing and analyzing the data collected from these sensors [10, 11]. Yet, several of these methods still depend on centralized systems for data storage and processing, which introduces problems regarding data security, flexibility, cost, and accessibility [12, 13]. Although some studies have explored the use of blockchain to secure data transfers, they mostly do not implement DL models for the real-time decision-making process based on soil health parameters [14, 15]. This work addresses these gaps by integrating IoT, blockchain, and DL models into the timely fertilizer distribution and constructing a secure system for monitoring greenhouse conditions.

The main contributions of this work are as follows:

- A novel way of optimizing fertilizer dispensing in the greenhouse environment using IoT sensors, blockchain technology, and DL models to monitor soil health is proposed. It provides accurate soil monitoring and secure data collection and storage to improve fertilizer dispensing accuracy.
- The proposed method uses the Lempel Ziv Welch (LZW) compression method for efficient data storage and transmission. In addition, the use of the SHA-3 (Keccak) hashing algorithm with a chaotic key for data encryption contributes to the improvement of security and makes the system robust against cryptographic attacks.
- This work introduces a DL model defined as a DL-CNN used to predict the soil pH values and NPK levels. Hence, the impact of the application of fertilizers can be determined.

- We have developed a Decentralized Application (D-App) dashboard that provides real-time data regarding soil health and greenhouse parameters. The application allows farmers and other stakeholders to view the key information, make decisions about fertilizer application, and consequently care for the best growing conditions.

The structure of this paper is organized as follows: Section II provides a literature review covering advancements in smart agriculture and the application of blockchain and DL. Section III details the proposed methodology for optimizing fertilizer dispensing using a blockchain method for secure smart greenhouse management. Section IV presents the results and analysis. Finally, Section V concludes the paper.

II. Literature Review

This section examines and explores different modern techniques, technologies, and weaknesses in smart agriculture to improve soil management, crop yield, and overall farm efficiency.

A. Emerging Techniques in Sustainable Agriculture

Wei et al. [16] demonstrated the utility of Capacitive Coupled Contactless Conductivity Detection (C4D) in soil nutrient detection. This method encompasses C4D data and cluster analysis to improve nutrient monitoring and management. Despite that, a very low level of nutrients can limit the method's performance, and the system's efficiency may vary due to different soils.

Thorat et al. [17] proposed the Transition Probability Function (TPF) and Convolutional Neural Network (CNN) for precision farming. In this work, a system identifies pests, prescribes insecticides, and examines the soil nutrients to indicate the most suitable fertilizers. However, the model lacks the integration of sensors like pH, temperature, humidity, and soil moisture sensors to capture a range of environmental data.

Senapaty et al. [18] suggested an IoT-enabled soil nutrient classification and crop recommendation (IoTSNA-CR) system. This model encompassed IoT sensors, cloud storage, and a multi-class support vector machine (MSVM) to classify soil nutrient levels. However, drawbacks include the need for significant investment in sensors and the need to clean data, which is a big challenge.

Pechlivani et al. [19] have coined soil and environmental monitoring using an IoT-enabled device with sensors to collect data on key soil and environmental parameters. The summation of sensors paired with an ESP32 microcontroller, data visualization, an Android app, and 3D printing for control housing. However, the study has inaccuracies in the sensor measurements and more validation in the different agricultural fields.

Indira et al. [20] proposed using Artificial Intelligence (AI), machine learning (ML), and Long-Range (LoRa) technology to transform farming operations. They analyzed these data using AI to provide actionable insights for improving agricultural practices. Nevertheless, challenges stem from issues such as data security and the difficulty of deploying AI in remote areas with limited internet connectivity.

Vincent et al. [21] introduced IoT and Al in agriculture to evaluate land suitability for cultivation. This technique is used for sensor networks to collect data on soil and environmental variables. It also uses the Multi-Layer Perceptron (MLP) neural networks to classify data into four suitability classes. This study has limitations due to incomplete sensor data and overfitting in the MLP model due to its complexity.

Singh et al. [22] focused on developing a portable device for soil nutrient analysis. This method detects soil nitrogen (N) and phosphorus (P) levels to optimize crop yield and minimize fertilizer use integrated with IoT and LED sensors. Yet, its limitations include potential inaccuracies at higher nutrient concentrations and the need for further refinement to improve sensitivity.

Morchid et al. [23] introduced the applications of IoT and sensor technology in agriculture and food security. The paper also enumerates IoT's advantages in agriculture, including efficiency and resource reduction. Nevertheless, it still cannot offer any real-world examples and only speculations about solutions to the challenges.

TABLE I. Analysis and Applications of Blockchain in Greenhouse Agriculture

References	Technique Used	Objectives	Results	Limitation
[26]	Blockchain and IoT	Enhance transparency and traceability in the agricultural process	Improved trust and reliability in food certification	High initial setup cost and complexity
[27]	DL-based Image Processing	Measurement and monitoring of greenhouse environmental parameters	98% success rate in image processing	Limited dataset size for training
[28]	ML (Random Forest)	Classify greenhouse gas (GHG) emissions during groundnut harvesting	Accuracy: 86.46%	Limited by data variability and missing values
[29]	Blockchain and IoT	Ensure anonymity and security in e-voting	High voter privacy and verifiability	Requires computational resources
[30]	RNN and · Blockchain	Secure agricultural data in IoT network	Accuracy: 97.7%,	Design complexity
[31]	Blockchain- consensus algorithm	Ensure a secure and transparent supply chain in smart agriculture	Reduced fraud and counterfeiting	High computational cost
[32]	Blockchain and DL	Ensure food safety and transparency in the supply chain	RMSE values of 872.56	Increased implementation costs
[33]	ML: Multi-regression analysis	Identify the next hop for agricultural data transferring	Improved energy usage efficiency by 13% and 16%	High packet congestion

Nayagam et al. [24] addressed the issue of controlling disease in smart agriculture with IoT technology. It suggested using multiple GPUs in a Parallel and Distributed Simulation Framework (PDSF) with IoT to oversee crop surveillance and pest management. However, multiple GPUs could reduce system performance, and more efficient data processing algorithms are also needed.

Rajak et al. [25] suggested the integration of IoT and smart sensors in agriculture for crop production and minimizing economic losses. Techniques like AI algorithms and ML are used for real-time data processing and precision farming. Yet, high implementation costs and data security concerns impact farmers by making the technology less accessible.

B. Blockchain Integration in Sustainable Agriculture

The literature shows advanced agricultural techniques for improving agricultural practices with several limitations (as shown in Table I). This work proposes an integrated IoT, blockchain, and DL approach to solve this issue to improve soil management and optimize greenhouse agriculture.

III. Proposed Methodology for Optimal and Appropriate Fertilizer Dispensing

The proposed system optimizes fertilizer dispensing by accurately assessing soil conditions. This model employs IoT sensors at different greenhouses to collectively monitor soil nutrition and pH values. The collected data from these sensors is compressed and assigned to the IPFS hash code for secure transfer to the blockchain, specifically in an off-chain setup. This data is transferred to the blockchain using MetaMask for registration and login authentication. Once transferred to the blockchain, the data is input into a Convolutional Neural Network (DL-CNN) model to classify pH value and NPK (Nitrogen, Phosphorous, Potassium) amount in the soil to apply the required fertilizer. The DL model's output can be accessed through a dashboard in a Decentralized Application, thereby providing insights to consumers, field analysts, and agricultural organizations. The Field analysts can use this data for activating the control center which further implements the necessary solutions within the greenhouse environment to provide necessary solutions for using appropriate fertilizer for optimal growing conditions. Fig. 1 explains the overall workflow of this system. It integrates IoT sensors, blockchain technology, and DL models to accurately assess soil conditions and optimize fertilizer application in greenhouse environments.

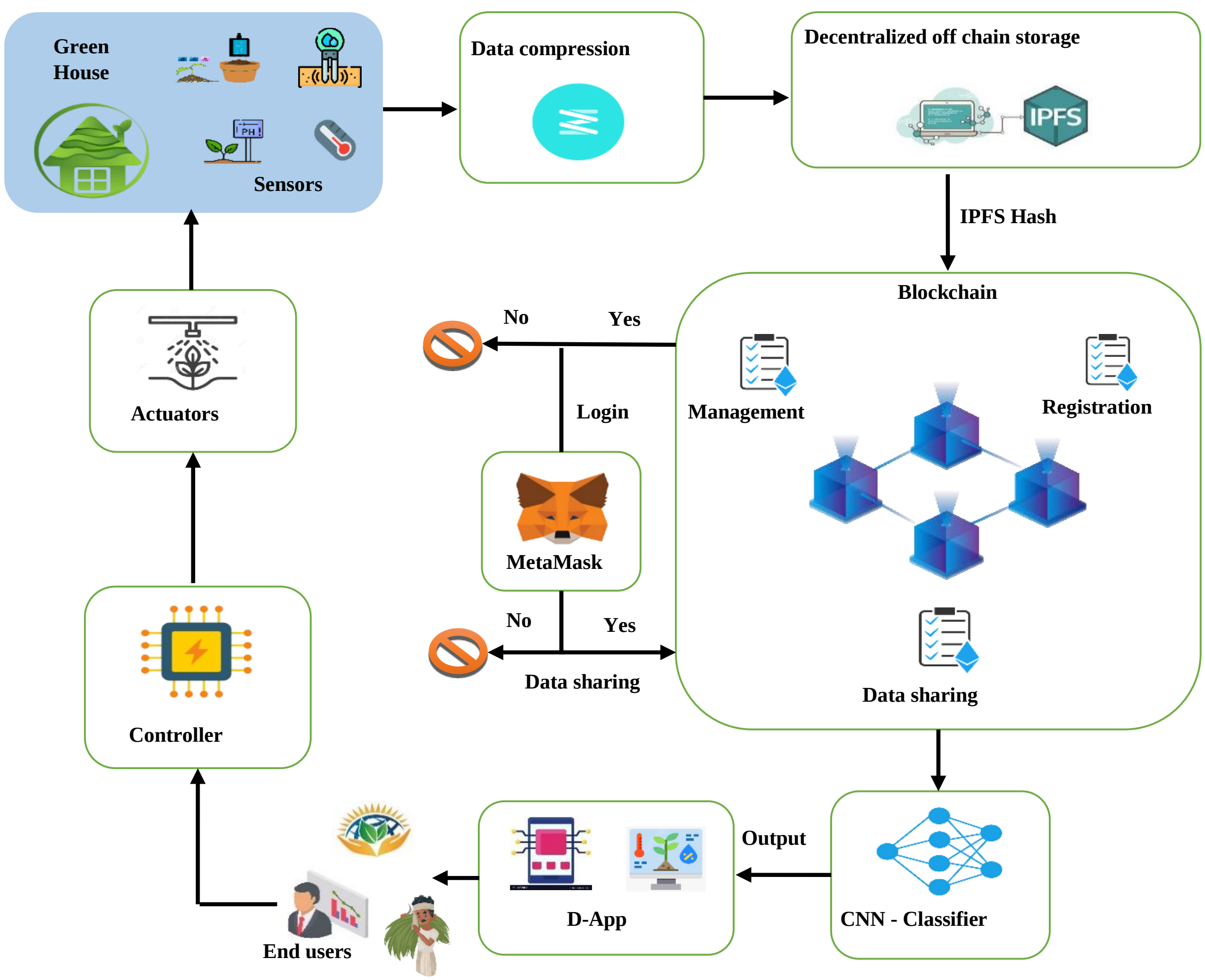


Fig. 1. Workflow of the proposed system.

A. Data Collection

In this framework, IoT sensors, including pH, moisture, temperature, and soil nutrients, are placed across different greenhouses to continuously monitor and collect data on soil conditions. These sensors capture real-time data that reflects the dynamic conditions of the greenhouse environment to provide a dataset for assessing soil health and making informed decisions on resource management.

B. Data Processing

The collected sensor data is compressed using the Lempel-Ziv-Welch (LZW) technique [34] to store large data volumes efficiently. LZW compresses data by replacing repeated sequences of characters with shorter codes. It takes a dictionary filled with all single-character strings. Meanwhile, it checks each sequence against this dictionary. If the sequence is found, it is expanded with the next character and continues. Otherwise, the sequence is added to the dictionary, and the code for the previous sequence is output.

C. Blockchain Configuration

1) Data Collection and IPFS Storage: After the compressed data is collected, it is securely assigned an IPFS (Inter-Planetary File System) hash code for securely storing off-chain. IPFS enables distributed storage, in which data is divided up into small parts, and each is signed with a cryptographic hash using the Keccak-256 algorithm [35]. Such chunks are then shared among several IPFS networks.

2) MetaMask with blockchain integration: Here, MetaMask provides secure data to be transferred to the blockchain through registration and log-in authentication. It makes use of Keccak hashing. If data chunks are stored in IPFS, their hash codes are recorded on the blockchain. Hence, it provides a secure reference to the off-chain data, whereas the blockchain storage requirements are minimized. To improve security, the SHA-3 (Keccak-256) hashing algorithm is used for the encryption process and is combined with the chaotic key for encryption and decryption. A chaotic key, generated with the help of logistic maps, is integrated with the SHA-3 hash to create a secure and unpredictable hash resistant to cryptanalysis attacks. Moreover, this algorithm is used to encrypt IoT devices with low computing resources, which are decrypted upon reaching the blockchain and fed into the DL-CNN model.

Fig. 2 provides the data flow and security mechanisms in this setup. The encrypted data is stored off-chain using IPFS and securely transferred through MetaMask. The data undergoes blockchain validation to improve security for real-time decision-making.

D. Data Classification

1) Data preprocessing: Before the classification step, the data goes through initial processing steps to ensure the optimal format for analysis. Eventually, the Z-score normalization method [36] eliminates the effect of outliers by standardizing the data to have a mean of zero and a standard deviation of one to reduce the influence of extreme values. After that, a Label Encoder [37] is applied to change the strings of the categorical values into integer numbers, thereby enabling numerical analysis. Following this, the One-Hot Encoder transforms these categorical integers into binary format to create a sparse matrix where each category is represented as a separate binary column.

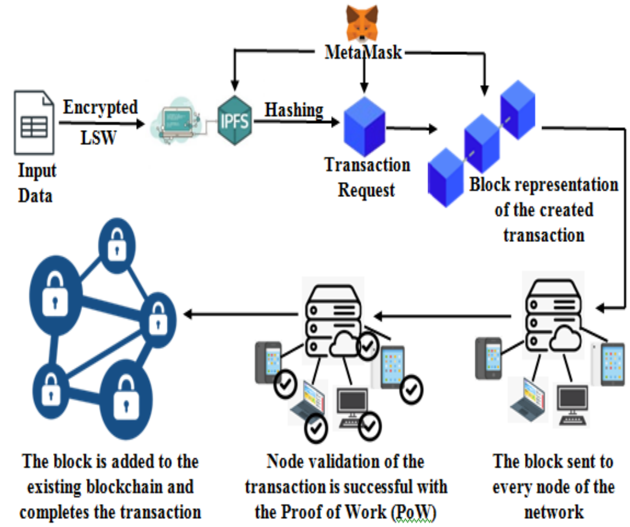


Fig. 2. Blockchain-based data transfer workflow.

2) Classification: The binary numerical data processed through preprocessing is loaded into the DL-CNN [37] model, which predicts the pH (soil acidity or alkalinity) and NPK content (determining the nutrition value of the soil). The CNN architecture features several levels structured for capturing and classifying important data. It starts with a 55*55*3 input layer which are the dimensions of the feed data. This is followed by multiple convolutional layers with different sizes of filters as (4*4) or (3*3). It identifies various features caught in the data. The batch normalization layer is placed after each convolutional layer to improve the stability of learning, and the activation layer employs the P-ReLU function to inject non-linearity. Pooling layers are inserted to reduce the spatial dimensions, decrease the computational cost, and improve the quality of feature extraction. As the network progresses through these layers and captures more intricate patterns in the data. A dropout layer is implemented to avoid overfitting wherein neurons are randomly disrupted with a fraction of them deactivated during training. Finally, the model contains a fully connected layer and a regression layer using Error Regression that classifies the final labeling (soil pH and nutrient content) to recommend the optimal fertilizers.

3) Visualization: The outputs from the DL-CNN model are visualized through the dashboard within a Decentralized Application (D-App). This dashboard offers a user interface for the customers, the field researchers, and the agricultural organizations to access real-time information on soil health, such as pH values and NPK content. By displaying these results in an accessible format, stakeholders understand the soil's condition and make informed decisions regarding fertilizer application and plan crop management.

4) Control center activation: Based on the dashboard's analysis results, field analysts can activate the control center to require modifications within the greenhouse environment. This can involve applying the appropriate amount of fertilizer to improve the quality of the soil and crop growth so that plants receive the nutrients they need for optimal development.

IV. Results and Discussion

The proposed system was implemented on a blockchain platform integrated with Python, utilizing smart contracts and secured data for accurate data handling. The results show the system can accurately classify soil pH and NPK levels, thus enabling precise fertilizer application while maintaining data integrity and security through blockchain technology.

A. Dataset Description

This dataset consists of one million soil samples that have been simulated from different places across the world. Each sample comes with information about soil texture, pH, organic matter content, moisture content, bulk density, nutrient levels (N, P, K), cation exchange capacity, electrical conductivity, color, porosity, and water holding capacity. This dataset, which has been developed for environmental scientists, agronomists, and data scientists, is excellent for research, ML, DL models, and educational purposes.

Dataset link: Global Soil Characteristics Dataset (1 Million) (kaggle.com).

B. Performance Analysis

Table II shows that compression techniques are effective in storing and transferring large volumes of sensor data to the blockchain in a compressed format. LZW ranks a balanced performance, compared to Huffman and Arithmetic. In its case, the LZW may show the best harmony with the compression efficiency and the speed of processing. Thus, it is a perfect choice for real-time applications, where a quick response time and a small storage footprint are crucial.

TABLE II. Comparative Analysis of Data Compression Techniques

Technique	Compression Ratio	Compression Time (s)	Compressed Size (bytes)	Memory Usage (bytes)
LZW	**2.108725**	**17.37507**	**1.31E+08**	**1.31E+08**
Huffman	2.398807	21.33783	1.16E+08	1.16E+08
Arithmetic	2.279311	226.2766	1.22E+08	1.22E+08

Fig. 3 demonstrates the Keccak-256 hash tool interface used in the system. It includes a text field with "Agriculture" which is the default text to be hashed. Below the input fields, "Hash" and "Auto Update" give the users the ability to generate and update the hash of the corresponding text. The resulting hash depicted as an alphanumeric string in the output field proves the capability of the Keccak-256 hashing function in securely changing and verifying data.

Fig. 3. Keccak-256 hash tool interface.

Fig. 4 shows a transaction detail from a blockchain explorer. It shows the transaction hash, block number, block hash, contract address, sender and recipient addresses (partially blocked for privacy) the gas used, and input data details. This detailed view checks and observes the transactions carried on the blockchain to ensure security in the management of digital assets within the system.

Fig. 5 illustrates a command line interface that exhibits a program execution output with data storage and verification. The screen displays, "Files are stored in local server" and "Data is already stored for this file name," then "wait - compiling/applying successfully in 65ms (51 modules)" and "true," which means that the "Hash is Stored in a Smart Contract". This output expresses the process of collecting and whether the data is correctly stored. Thus, by proving that the system records the data and verifies it in a blockchain setting.

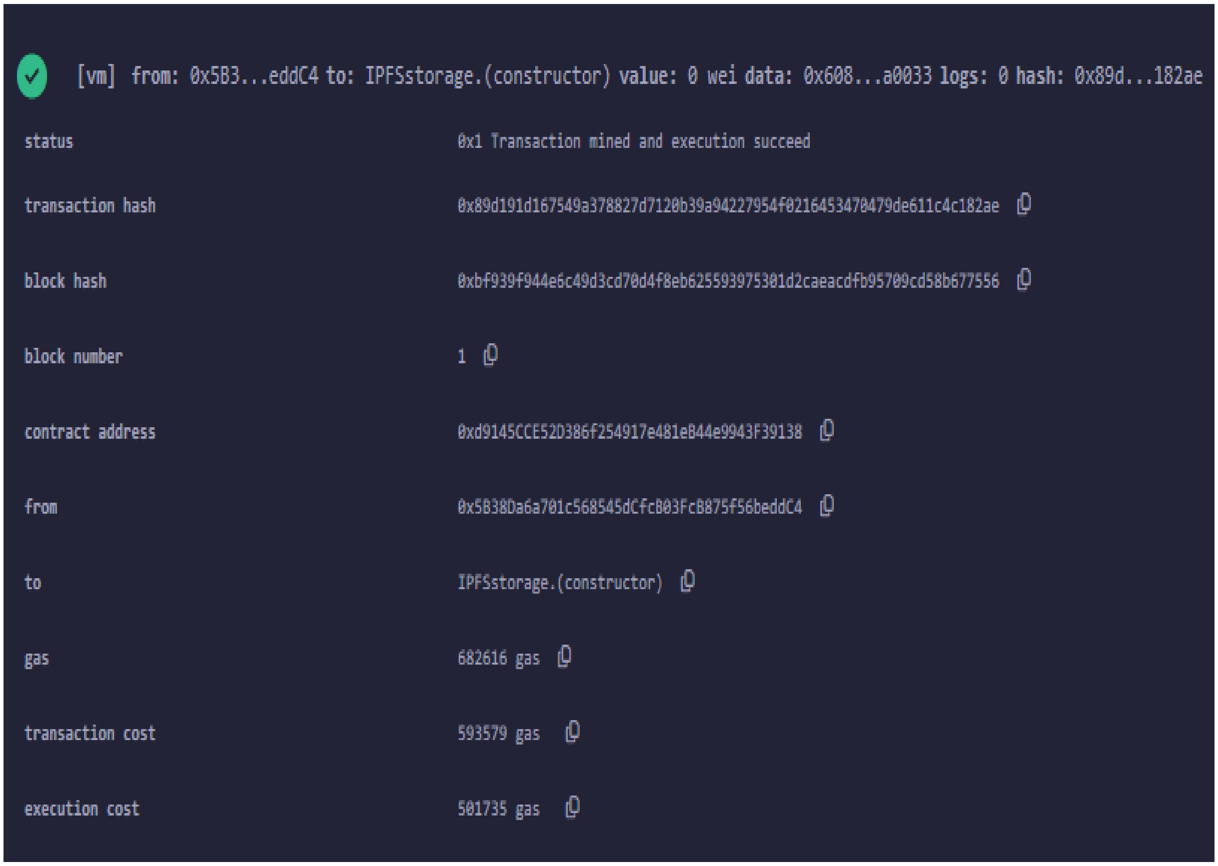


Fig. 4. Blockchain transaction details.

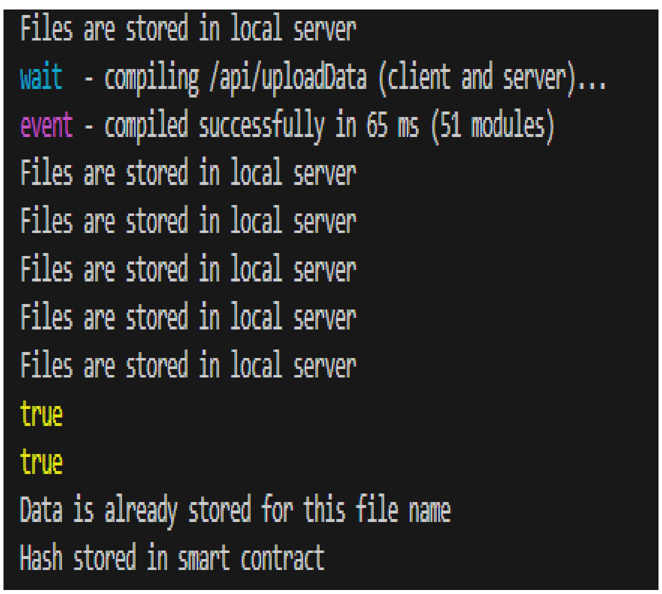


Fig. 5. Execution output for data storage and verification.

Fig. 6 shows the performance of a DL-CNN model employed for predicting soil states as well as determining the need for fertilizers. Specifically, the metrics of accuracy (98.86%), precision (98.3%), sensitivity (98.3%), specificity (99.15%), F-measure (98.3%), Matthews-correlation coefficient (97.45%), and the negative predictive value (99.15%) highlight the model performance in soil condition classification. This in-depth evaluation establishes the model's high dependability and precision, which are necessary for ensuring accurate fertilizer recommendations.

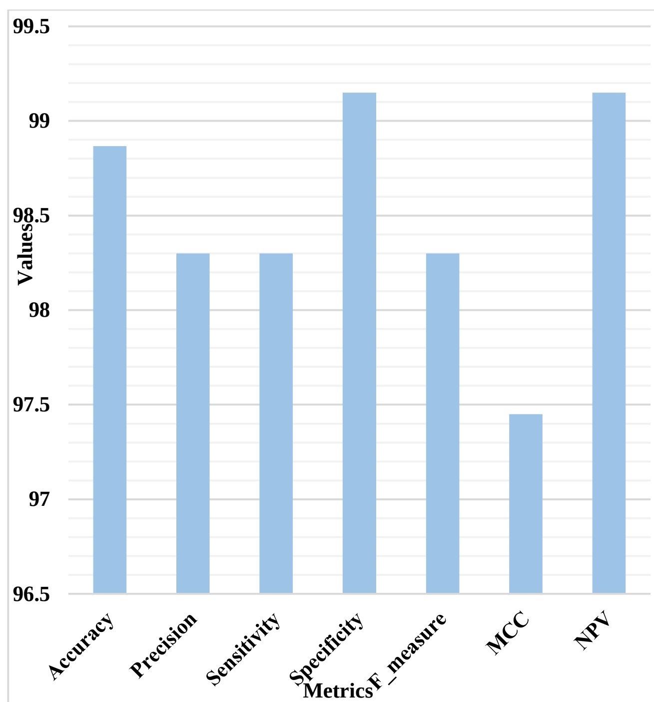


Fig. 6. Performance metrics of the DL-CNN classification model.

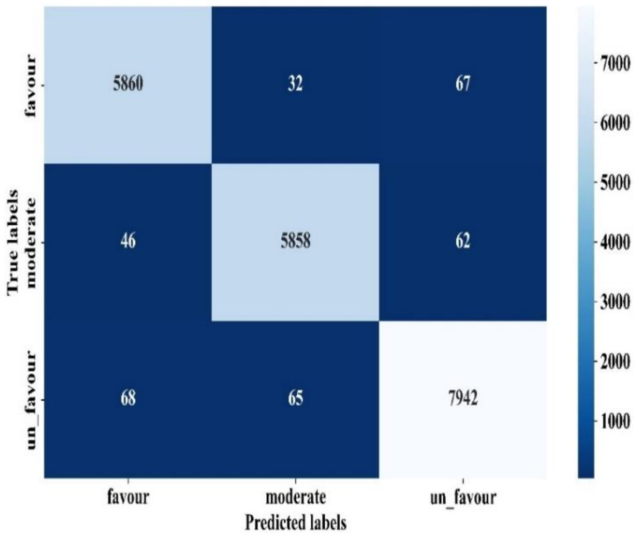
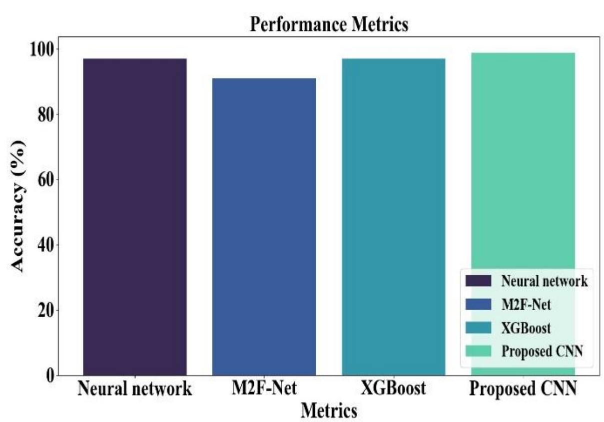


Fig. 7. Confusion matrix for DL-CNN classification model.

Fig. 7 presents a confusion matrix in evaluating the classification model's performance in predicting soil conditions. This matrix compares actual target values with the model's predictions across three classes: 'favor,' 'moderate,' and 'un favor.' The diagonal cells represent correctly classified instances. It indicates the model's accuracy for each class, while the off-diagonal cells reveal misclassifications, indicating areas where the model's predictions deviate from actual values. This evaluation gauges the applicability of DL- CNN in the classification of soil pH and NPK by facilitating improvement for accurate fertilizer recommendations.



A suitable name for this figure could be:

Fig. 8. Accuracy comparison for soil condition analysis.

Fig. 8 presents a comparison of the performance of various state-of-the-art methods in terms of accuracy for soil condition analysis. Neural Network [38] with a result of 97%, while Multimodal Fusion Network (M2F-Net) [39] with a score of 91%, and eventually, XGBoost [40] with 97%. At last, the proposed CNN tops the list with an accuracy of 98.86% among all the methods being compared. This outstanding performance of the model is traced back to its architecture, which, in developing CNN, allows it to better identify soil pH and nutrient content classifications.

C. Discussion

This part is intended to demonstrate the proposed system's excellent abilities and working. Fig. 3 uses the Keccak-256 hash tool interface that models the secure hash function of data for trust in blockchain. Fig. 4 shows a detailed view of blockchain transaction information, thereby proving the secure administration and verification of transactions. Fig. 5 shows the output of data storage and verification, which firmly says that the storage of data on the blockchain and the fact that it was validated were successful. Fig. 6 shows the platform with the best performance, with the DL-CNN model reaching the highest accuracy of 98.86%. Thus, it is the most effective method when doing soil condition analysis and fertilizer recommendations. The confusion matrix of Fig. 7 is lastly used to provide the model's accuracy and identify the weak points in the model. Finally, various state-of-the-art methods can be compared with the proposed CNN, which has the highest accuracy and ability to classify soil pH and nutrient content. These results, in totality, assure the productivity and the benefits of relating IoT, blockchain, and DL technologies in smart agriculture to precision and security.

V. Conclusion

This research presents a revolutionizing system for making fertilizer use efficient in sustainable agriculture through the integration of IoT sensors, blockchain technology, and a DL-CNN. The suggested technique effectively addresses key challenges such as lack of data security and precise allocation of resources. The system uses IoT sensors to keep track of soil conditions and the IPFS and blockchain for secure data storage and transfer which guarantees the data conforms data integrity and confidentiality. The DL-CNN model delivers 98.86% classification accuracy, thus highlighting its capability for soil pH and nutrient levels evaluation. The real-time information given by a DE App to make the right decisions about the amount of fertilizer required for soil fertility improvement and, consequently, higher crop yields. Overall, this framework offers a solution for modernizing fertilizer management in agriculture, combining advanced technology with practical applications, guaranteeing increased agricultural output and sustainability. Nonetheless, unsuitable sensors can mislead outcomes, which can significantly impede the system's performance. Further research is likely to cover the remote sensing tools for pest detection and the possibility of the use of drone type of technology for precise water application.

References

[1] Kaur, A., Bhatt, D.P. and Raja, L., 2024. Developing a Hybrid Irrigation System for Smart Agriculture Using IoT Sensors and Machine Learning in Sri Ganganagar, Rajasthan. *Journal of Sensors*, *2024*(1), p.6676907.

[2] Rahaman, M., Lin, C.Y., Pappachan, P., Gupta, B.B. and Hsu, C.H., 2024. Privacy-Centric AI and IoT Solutions for Smart Rural Farm Monitoring and Control. *Sensors*, *24*(13), p.4157.

[3] Md. Mamun Hossain, Md. Ashiqur Rahman, Sudipto Chaki, Humayra Ahmed, Ahsanul Haque, Iffat Tamanna, Sweety Lima, Most. Jannatul Ferdous and Md. Saifur Rahman, "Smart-Agri: A Smart Agricultural Management with IoT-ML-Blockchain Integrated Framework" International Journal of Advanced Computer Science and Applications (IJACSA), 14(7), 2023. http://dx.doi.org/10.14569/IJACSA.2023.01407107.

[4] Aliyu, A.A. and Liu, J., 2023. Blockchain-Based Smart Farm Security Framework for the Internet of Things. *Sensors*, *23*(18), p.7992.

[5] Akella, G.K., Wibowo, S., Grandhi, S. and Mubarak, S., 2023. A systematic review of blockchain technology adoption barriers and enablers for smart and sustainable agriculture. *Big Data and Cognitive Computing*, *7*(2), p.86.

[6] Lv, G., Song, C., Xu, P., Qi, Z., Song, H. and Liu, Y., 2023. Blockchain-based traceability for agricultural products: a systematic literature review. *Agriculture*, *13*(9), p.1757.

[7] Chen, H.Y., Sharma, K., Sharma, C. and Sharma, S., 2023. Integrating explainable artificial intelligence and blockchain to smart agriculture: Research prospects for decision making and improved security. *Smart Agricultural Technology*, *6*, p.100350.

[8] T C Jermin Jeaunita, Sarasvathi V, Fault Tolerant Sensor Node Placement for IoT based Large Scale Automated Greenhouse System, International Journal of Computing and Digital Systems, 8-2, 2019. http://dx.doi.org/10.12785/ijcds/080210

[9] Sabir Hussain Awan, Sheeraz Ahmed, Asif Nawaz, Sozan Sulaiman Maghdid, Khalid Zaman, M.Yousaf Ali Khan, Zeeshan Najam and Sohail Imran, “BlockChain with IoT, an Emergent Routing Scheme for Smart Agriculture” International Journal of Advanced Computer Science and Applications(IJACSA), 11(4), 2020. http://dx.doi.org/10.14569/IJACSA.2020.0110457

[10] Araújo, S.O., Peres, R.S., Ramalho, J.C., Lidon, F. and Barata, J., 2023. Machine learning applications in agriculture: current trends, challenges, and future perspectives. *Agronomy*, *13*(12), p.2976.

[11] Syed, L., 2024. Smart Agriculture using Ensemble Machine Learning Techniques in IoT Environment. *Procedia Computer Science*, *235*, pp.2269-2278.

[12] Adli, H.K., Remli, M.A., Wan Salihin Wong, K.N.S., Ismail, N.A., González-Briones, A., Corchado, J.M. and Mohamad, M.S., 2023. Recent advancements and challenges of AIoT application in smart agriculture: A review. *Sensors*, *23*(7), p.3752.

[13] Alahmad, T., Neményi, M. and Nyéki, A., 2023. Applying IoT sensors and big data to improve precision crop production: a review. *Agronomy*, *13*(10), p.2603.

[14] Naseer, A., Shmoon, M., Shakeel, T., Ur Rehman, S., Ahmad, A. and Gruhn, V., 2024. A Systematic Literature Review of the IoT in Agriculture-Global Adoption, Innovations, Security Privacy Challenges. *IEEE Access*.

[15] Taji, K. and Ghanimi, F., 2024. Enhancing security and privacy in smart agriculture: A novel homomorphic signcryption system. *Results in Engineering*, *22*, p.102310.

[16] Wei, Y., Wang, R., Zhang, J., Guo, H. and Chen, X., 2023. Partition management of soil nutrients based on capacitive coupled contactless conductivity detection. *Agriculture*, *13*(2), p.313.

[17] Thorat, T., Patle, B.K. and Kashyap, S.K., 2023. Intelligent insecticide and fertilizer recommendation system based on TPF-CNN for smart farming. *Smart Agricultural Technology*, *3*, p.100114.

[18] Senapaty, M.K., Ray, A. and Padhy, N., 2023. IoT-enabled soil nutrient analysis and crop recommendation model for precision agriculture. *Computers*, *12*(3), p.61.

[19] Pechlivani, E.M., Papadimitriou, A., Pemas, S., Ntinas, G. and Tzovaras, D., 2023. IoT-based agro-toolbox for soil analysis and environmental monitoring. *Micromachines*, *14*(9), p.1698.

[20] Indira, P., Arafat, I.S., Karthikeyan, R., Selvarajan, S. and Balachandran, P.K., 2023. Fabrication and investigation of agricultural monitoring system with IoT & AI. *SN Applied Sciences*, *5*(12), p.322.

[21] Vincent, D.R., Deepa, N., Elavarasan, D., Srinivasan, K., Chauhdary, S.H. and Iwendi, C., 2019. Sensors driven AI-based agriculture recommendation model for assessing land suitability. *Sensors*, *19*(17), p.3667.

[22] Singh, H., Halder, N., Singh, B., Singh, J., Sharma, S. and Shacham-Diamand, Y., 2023. Smart farming revolution: portable and real-time soil nitrogen and phosphorus monitoring for sustainable agriculture. *Sensors*, *23*(13), p.5914.

[23] Morchid, A., El Alami, R., Raezah, A.A. and Sabbar, Y., 2023. Applications of internet of things (IoT) and sensors technology to increase food security and agricultural Sustainability: Benefits and challenges. *Ain Shams Engineering Journal*, p.102509.

[24] Nayagam, M.G., Vijayalakshmi, B., Somasundaram, K., Mukunthan, M.A., Yogaraja, C.A. and Partheeban, P., 2023. Control of pests and diseases in plants using iot technology. *Measurement: Sensors*, *26*, p.100713.

[25] Rajak, P., Ganguly, A., Adhikary, S. and Bhattacharya, S., 2023. Internet of Things and smart sensors in agriculture: Scopes and challenges. *Journal of Agriculture and Food Research*, *14*, p.100776.

[26] Hasan, H.R., Musamih, A., Salah, K., Jayaraman, R., Omar, M., Arshad, J. and Boscovic, D., 2024. Smart agriculture assurance: IoT and blockchain for trusted sustainable produce. *Computers and Electronics in Agriculture*, *224*, p.109184.

[27] Frikha, T., Ktari, J., Zalila, B., Ghorbel, O. and Amor, N.B., 2023. Integrating blockchain and deep learning for intelligent greenhouse control and traceability. *Alexandria Engineering Journal*, *79*, pp.259-273.

[28] El Hathat, Z., Venkatesh, V.G., Sreedharan, V.R., Zouadi, T., Manimuthu, A., Shi, Y. and Srinivas, S.S., 2024. Leveraging Greenhouse Gas Emissions Traceability in the Groundnut Supply Chain: Blockchain-Enabled Off-Chain Machine Learning as a Driver of Sustainability. *Information Systems Frontiers*, pp.1-18.

[29] Toma, C., Popa, M., Boja, C., Ciurea, C. and Doinea, M., 2022. Secure and anonymous voting D-app with IoT embedded device using blockchain technology. *Electronics*, *11*(12), p.1895.

[30] Mahalingam, N. and Sharma, P., 2024. An intelligent blockchain technology for securing an IoT-based agriculture monitoring system. *Multimedia tools and applications*, *83*(4), pp.10297-10320.

[31] Srikanth, M., Mohan, R.J. and Naik, M.C., 2023. Blockchain-based consensus for a secure smart agriculture supply chain. *European Chemical Bulletin*, *12*(4), pp.8669-8678.

[32] Khan, Prince Waqas, Yung-Cheol Byun, and Namje Park. "IoT-blockchain enabled optimized provenance system for food industry 4.0 using advanced deep learning." Sensors 20, no. 10 (2020): 2990.

[33] Saba, T., Rehman, A., Haseeb, K., Bahaj, S.A. and Lloret, J., 2023. Trust-based decentralized blockchain system with machine learning using Internet of agriculture things. *Computers and Electrical Engineering*, *108*, p.108674.

[34] Hassan, A., Javed, S., Hussain, S., Ahmad, R. and Qazi, S., 2024. Arithmetic N-gram: an efficient data compression technique. *Discover Computing*, *27*(1), p.1.

[35] Ali, Alaa Abid Muslam Abid, Manar Joundy Hazar, Mohamed Mabrouk, and Mounir Zrigui. "Proposal of a Modified Hash Algorithm to Increase Blockchain Security." *Procedia Computer Science* 225 (2023): 3265-3275.

[36] Kosuru, V.S.R. and Kavasseri Venkitaraman, A., 2023. A smart battery management system for electric vehicles using deep learning-based sensor fault detection. *World Electric Vehicle Journal*, *14*(4), p.101.

[37] Abbas, S., Sampedro, G.A., Abisado, M., Almadhor, A., Kim, T.H. and Zaidi, M.M., 2023. A Novel Drug-Drug Indicator Dataset and Ensemble Stacking Model for Detection and Classification of Drug-Drug Interaction Indicators. *IEEE Access*.

[38] Musanase, C., Vodacek, A., Hanyurwimfura, D., Uwitonze, A. and Kabandana, I., 2023. Data-driven analysis and machine learning-based crop and fertilizer recommendation system for revolutionizing farming practices. Agriculture, 13(11), p.2141.

[39] Dhakshayani, J. and Surendiran, B., 2023. M2F-Net: A deep learning-based multimodal classification with high-throughput phenotyping for identification of overabundance of fertilizers. Agriculture, 13(6), p.1238.

[40] Senapaty, Murali Krishna, Abhishek Ray, and Neelamadhab Padhy. "A decision support system for crop recommendation using machine learning classification algorithms." Agriculture 14, no. 8 (2024): 1256.