

Blockchain-Assisted Modular and Scalable Precision Agriculture System With Internet of Thing Systems

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Abstract

The demanding challenges like data privacy, scalability and real-time decision-making can be addressed with an influential method by integrating federated learning and blockchain to make agricultural system to be smarter. These serious challenges are addressed in this paper by proposing a novel framework named AgriTrustChain++. The proposed method is a hybrid method and an integration of smart contract automation, federated edge intelligence and permissioned blockchain. There are five layers in the proposed framework, which include application layer, smart contract layer, blockchain layer, federated intelligence layer and IoT edge layer. The proposed system performs local computations securely and also preserves the end-to-end traceability with faster decision-making capability. TensorFlow Federated and Hyperledger are used in the implementation. A total of 3,000 records are used in the simulation process, where IoT and edge devices over 15 crop cycles are considered. The proposed system is evaluated and exhibits a throughput of 110 records/s, 27% energy conservation, 92.5% accuracy and 1.8 s average latency. The performance of the proposed system, AgriTrustChain++, is compared with AgriFusion and AgriLedger and is shown to be outperforming.

Categories: Blockchain and Cryptocurrency, Predictive Analytics, IoT Applications

Keywords: precision agriculture, iot sensors, smart contracts, federated learning, block chain technology

Introduction

With critical challenges like unpredictable climate, pressures from the global market, and limited resources, it is becoming difficult to produce the required amount of food on time. Hence, more transformations are taking place and need to be taken in modern agriculture [1-3]. There is a deficiency of efficiency, transparency, and also faith among various stakeholders like consumers, distributors, and farmers in the case of traditional farming, even though it is ubiquitous. In most cases, the details regarding the amount of crop produced, sales taken place, amount of crop in storage, and expenditure on storage and transport are split, prone to error, and susceptible to manipulation. These issues will definitely minimize efficiency in crop production, cause wastage of food, result in unfair pricing, and raise concerns about safety [4-7].

The latest technologies like blockchain and Internet of Things (IoT) [1-3] will help in dealing with these concerns in agriculture and hence are widely being incorporated. Blockchain technology helps in securing the data that need to be shared among various stakeholders, while IoT system is used to monitor the condition of soil, crop, weather, etc., in real time. The decision-making process can be made efficient using the precise data in time with the combination of blockchain and IoT, which leads to precision agriculture. However, the integration of these two technologies is not challenge free in real-time systems [8-15].

Some studies [1,6,7] proved that the agriculture can be made transparent and consistent using blockchain technology, whereas some studies [2,11,12] illustrated that the data can be collected in real time using IoT devices.

Intelligent, decentralized and secure systems can be developed with the integration of these technologies, IoT and blockchain [3,8,9]. Nevertheless, there are some critical drawbacks with the existing systems. Most of them do not have privacy control, are not scalable, and are dependent on infrastructure that consumes more power, which cannot be afforded by most farmers [4,5,15].

For instance, Ethereum-like public blockchains have been used in some systems, where they require more energy and the speed of transactions is low. Prediction of patterns in weather, prices of various crops in the market and outbreaks of crop diseases need to be carried out accurately and effectively, which fails in some systems because of a lack of smart analytics. The data becomes incorrect if the IoT sensors are

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compromised, and there is no use in using blockchain technology to secure wrong data. Furthermore, there is no control for farmers over the accessibility of the data [10,13,14].

In this paper, AgriTrustChain++ framework is proposed to resolve the issues in the existing systems, and this framework helps in improving the security, intelligence and scalability of the system when compared to the legacy systems. The technologies like federated machine learning, predictive edge computing and permissioned blockchains with smart contracts are integrated in the proposed framework. These technologies supports in effective energy conservation, privacy in design and adaptability to various farming atmospheres of the agriculture system.

Specifically, a layered architecture is introduced in the proposed framework, AgriTrustChain++. A private blockchain is used by cooperatives, logistic providers and regulatory bodies, whereas the public layer is for interaction between suppliers and customers. Both transparency and privacy are provided with this layered architecture. By incorporating federated learning in the layered architecture, raw data need not be sent to the cloud, and AI models can be trained using local devices, which avoids risks and protects users' privacy [16-20]. Trivial encryption and access control based on roles are also incorporated to ensure that data can be viewed, modified, or updated only by authorized users [17-24].

It is also important that the food system needs to be traced. This is focused on by Hang et al. [9] and Cao et al. [23]. In the proposed framework, logs based on blockchain are used to track the system at every stage, right from the first step, i.e., planting, to the final step, i.e., crop in the market. In the systems proposed by Dey and Shekhawat [7] and Chaganti et al. [8], the reliance is on centralized cloud systems, whereas this is reduced by incorporating processing at the edge. Additionally, in line with the efforts made by Khan et al. [16], Patel et al. [18], and Saba et al. [20], cost-effectiveness and the role of sustainability are considered in the proposed framework. As Krishna et al. [24] explored, low-powered and mobile devices are integrated into the proposed system, which is another exceptional feature. Hence, the deployment of the proposed system can be made in rural or remote regions as well. Another exclusive feature of the system is that it is designed to be modular, enabling further extensions.

Limited resources, increasing demands for food and unpredictable weather are issues faced by agriculture, but there is a deficiency of transparency, efficiency and trust in traditional systems. Even though existing IoT and blockchain solutions resolve some issues, they struggle with high energy use, scalability and privacy. To resolve these issues, AgriTrustChain++ is proposed in this paper as a hybrid framework where blockchain, edge intelligence, and federated learning are integrated to provide scalable, secure, and smarter farming.

Contributions of the paper

- Layered architecture, where privacy amid trusted parties is guaranteed by permissioned public blockchain and transparency is ensured among the public channels.
- Predictions, like alerts related to diseases and estimation of yield, are made intelligent without any compromise in the privacy of the data by integrating federated learning at the edge level.
- Encryption methods (AES-128 and Elliptic Curve Cryptography [ECC]) and access control based on roles are implemented for sharing data securely, ensuring that only authenticated users can access the data while consuming less energy.

The layered architecture of the proposed hybrid framework, AgriTrustChain++, which integrates the blockchain, edge intelligence and federated learning is the novelty of this paper. The models are trained locally, blockchain is used to guarantee trust and transparency, scalable Reliable, Replicated, Redundant and Fault-Tolerant (RAFT) consensus and lightweight encryption are used to attain energy efficiency. Intelligent automation, scalability and security are enabled for real-time smart agriculture with the proposed framework.

Related work

Critical challenges like data security, automation, trust and traceability in the agriculture field can be effectively handled by integrating IoT technologies and blockchain. Many researchers have shown that decisions taken during different steps in agriculture, right from production to distribution, can be handled effectively and modernized using these latest technologies. The chief advantages, such as traceable transactions and data immutability, are highlighted by Torky and Hassanein [1] with the use of IoT and blockchain in precision agriculture. The emphasis is on making the records of farming activities tamper-proof using blockchain.

The effective management of distributed farm data in real time is demonstrated with the help of distributed ledgers and the integration of blockchain with IoT sensors [2].

The contribution of communication, information and blockchain technologies to the development of smart farming systems is studied by Liu et al. [3]. Interoperability and scalability remain unsolved, even though more focus has been placed on transparency and automation; many existing models address these issues. Pradeep et al. [4,5] focused on minimizing computation-related delays in IoT networks, which they address by proposing edge-based task offloading models. These models are particularly appropriate for low-resource agricultural regions where power and bandwidth restrictions are severe. In the agriculture field, the integrity of data and the solidification of trust using blockchain are highlighted in reviews by many researchers.

Blockchain applications are studied by Lin et al. [6] and Dey and Shekhawat [7], projecting the capability to eradicate intermediaries, enhance data transparency, and minimize expenditure. A cloud-enabled blockchain framework is developed by Chaganti et al. [8] to securely monitor the status of crops during various steps in agriculture with the help of IoT devices. Analogous procedures are implemented in fish farming by Hang et al. [9], where blockchain-based certification is used to guarantee the legitimacy of production data.

Pincheira et al. [10] dealt with the monetary dimension of blockchain implementation by assessing the incorporation expenses in agri-food traceability schemes. The requirement for the deployment of lightweight blockchain models in real time is emphasized by highlighting the important tradeoff between operational expenses and the benefits of decentralization in their conclusions. A layered architecture named AgriFusion, which integrates emerging technologies, is developed and presented explicitly for precision agriculture by Li et al. [11]. Internet of Everything is implemented in agriculture by Babar and Akan [12], signifying a more general method involving data, processes and people. Even though the proposed method is capable, guidelines for implementing decentralized trust models are lacking in their architecture. Amraouy et al. [13] studied IoT frameworks based on blockchain and classified them according to their security features and technical architecture. This study highlights the significance of addressing privacy risks, power constraints, and heterogeneous devices in the deployment of blockchain in the agriculture sector.

Hu et al. [14] integrated edge computing and blockchain technology to present a framework for organic supply chain management. This framework focuses on post-harvest tracking and addresses confidence disasters in food systems.

Kharche et al. [15] applied blockchain technology to large-scale transport systems that share similarities with agricultural logistics. Nevertheless, they failed to deal with predictive tasks and analytics at sensor level. Khan et al. [16] offer performance optimization by integrating metaheuristics with blockchain during the analysis for smart agriculture; however, the incorporation of federated learning models is missing, which might further enhance performance.

Demestichas and Daskalakis [17] emphasize the importance of managing the data lifecycle in precision agriculture, where the quantity and velocity of data are huge. Permissioned blockchain with controlled access is used for the concepts that are extended in this paper, and the focus is on the systematic retrieval and storage. Blockchain technology is used to design a recommendation system to mention crop and guarantee that the endorsements are certifiable and unaffected to tampering.

With the integration of edge computing and blockchain, a smart agriculture system based on climatic conditions is developed by Wu [19]. The target or goal of this system is sensing the environment securely. In this system, the aggregation is done only after the climatic data is authenticated. Nonetheless, the analysis of data to advanced level and access control modularity is lacking. To incorporate trustworthiness in agriculture system that is based on IoT, Saba et al. [20] integrated the blockchain technology with machine learning techniques. Even though training procedures that are centralized are utilized, the work is aligned with federated learning method.

Adeboye et al. [21] proposed an advanced blockchain design for agriculture system, planning implementation enthusiasm across use cases. The important fields of consideration in his work are determined as trust of the stakeholder, regulatory alignment and interoperability. The integrated system of IoT and blockchain is developed for food supply chains and presented by Awan et al. [22]. This system supports the traceability systems that are distributed in nature. The analysis of the role of blockchain in the logistics of the agriculture is carried out by Cao et al. [23] and also the active adaptableness in smart contracts is contended. Krishna et al. [24] used learning automata to propose an early middleware design for precision agriculture, placing the foundation for context-aware and adaptive agricultural systems.

A novel hybrid recurrent Neural Elliptical Curve Blockchain model is proposed by Mahalingam and Sharma [25] to store agricultural data securely in the cloud. The input data is pre-processed, and continuous observation is facilitated using field monitoring module. Cryptographic analysis is performed to encrypt features to guarantee privacy before storing in the cloud.

IoT, blockchain and deep learning framework is proposed by Rahman et al. [26] to detect real-time pest in paddy cultivation. Deep learning model is used to enhance the performance, where IoT devices are used to gather field information using camera modules and transmissions are secured amid the cloud and devices using blockchain.

Sharma and Khullar [27] deployed a federated learning system on a blockchain ecosystem to provide secure communication in precision agriculture. IoT cyber-attacks that are prominent are detected, and, at the same time, the privacy is provided to the data. The trust is guaranteed by integrating Ethereum blockchain with IPFS, and collaborative learning is enabled. The performance parameters like accuracy, recall, precision and overall security are evaluated in diversified IoT environments.

Regardless of this detailed study, existing system failed in the end-to-end integration of data across various stages like distribution, validation, processing and collection. Most of the system utilized prototypes based on proof-of-concept or enforce restrictions in flexibility and scalability. There are two challenges that need to be addressed. One of which is the tradeoff amid privacy and transparency and the second is guaranteeing that IoT devices that are having limited power can efficiently involve in decentralized networks.

Hence, a hybrid framework, AgriTrustChain++, is introduced in this paper, which integrates the real-time capabilities of edge computing, the decentralized intelligence of federated learning and the privacy control of permissioned blockchain systems. With this process, it can deal with important and serious gaps of intelligent automation, energy efficiency and scalability, which are not explored in the existing research.

Table 1 presents the summary of limitations in related work.

Ref.	Contribution Area	Strengths	Gaps/Limitations
[1-3]	Blockchain + IoT for traceability	Immutable and tamper-proof records	Lack of scalability, interoperability
[4,5]	Edge computing models	Delay reduction in low-resource areas	No trust management or data integration
[6-9]	Blockchain for cost reduction and legitimacy	Transparency and secure certification	No predictive analytics or FL integration
[10,11]	Economic aspects, IoE integration	Cost-benefit tradeoff & broader context	Lacks decentralized trust implementation
[12,13]	Security architecture classification	Device-level security and risks mapped	Power constraints unresolved
[14,15]	Supply chain and logistics tracking	Real-time monitoring	Missing sensor-level analytics and forecasting
[16,20]	Optimization with AI/ML	Metaheuristics, ML with blockchain	No FL or decentralized training logic
[17,19]	Data lifecycle & climate-based systems	Permissioned access, environment sensing	No modular access control or analytics depth
[21-24]	System-level architecture	Interoperability, early middleware design	No end-to-end decentralized automation

TABLE 1: Summary of Limitations in Related Work
AI, Artificial Intelligence; FL, Federated Learning; IoT, Internet of Things; ML, Machine Learning

Materials And Methods

AgriTrustChain++ framework

The limitations of the traditional agricultural system are addressed by integrating lightweight encryption, federated edge intelligence and permissioned blockchain. Hence, the AgriTrustChain++ framework is presented in this section, which combines all these technologies. There are different modules in the AgriTrustChain++ framework, where each module shares one responsibility among various functionalities, extending from secure data acquisition to intelligent decision-making and transaction logging that can be traced.

The architecture of the proposed AgriTrustChain++ has five layers to guarantee security, smartness, real-time management of agricultural data and automation. The five fundamental layers of AgriTrustChain++, starting from the base layer to the top layer, are the IoT edge layer, federated intelligence layer, blockchain

layer, smart contract layer and application layer. Various devices that monitor weather, soil conditions, drones, environmental sensors, etc., are included in the IoT edge layer. Data such as soil moisture level, humidity, crop health, and temperature are sensed, gathered or collected by these devices, and pre-processing is performed on the devices themselves to filter out noise and normalize the data. Lightweight edge gateways can be used for pre-processing to reduce power consumption and bandwidth utilization. Above the IoT edge layer is the federated intelligence layer. Machine learning models are trained collectively by all the local edge nodes using local data in the federated intelligence layer. The outcome of this model is to recommend irrigation, obtain disease alerts and predict yield.

By avoiding the transfer of raw data to a centralized server, the privacy of the data is protected during the processes of yield forecasting, disease prediction, secure aggregation of model updates, reduction of communication overhead, and optimization of irrigation. Next to the federated intelligence layer is the blockchain layer. Hyperledger Fabric is used to implement a permissioned blockchain in this layer. The execution of smart contracts, sensor logs, and transactions are stored in the blockchain after verification, along with mechanisms for access control, which guarantees that only legitimate users can write to the blockchain. This builds trust among stakeholders and ensures auditability. The blockchain behaves as an immutable ledger, meaning nothing can be changed once recorded. Next is the Smart Contract Layer. This layer enables the execution of the rules that are predefined automatically.

Automation of the conditional operations like grant expenses, liberating insurance claims after confirmation of the damage, disease alerts is enabled, and entries of the adaptable supply chain based on the agreement rules are also automated. Finally, application layer consists of various web/mobile applications or dashboards to interact with different stakeholders like customers, distributors, government agencies and farmers. Also, stakeholders can access personalized services like real-time crop monitoring, supply chain tracing, product authenticity verification, and regulatory compliance.

Collectively, a vertical integrated system is formed using these layers, where data is transferred from one layer to other layer right from the field level sensor in IoT edge layer to high-level layer, i.e, application layer, which enables scalability, preserves privacy and automation driven architecture for smart and precision agriculture.

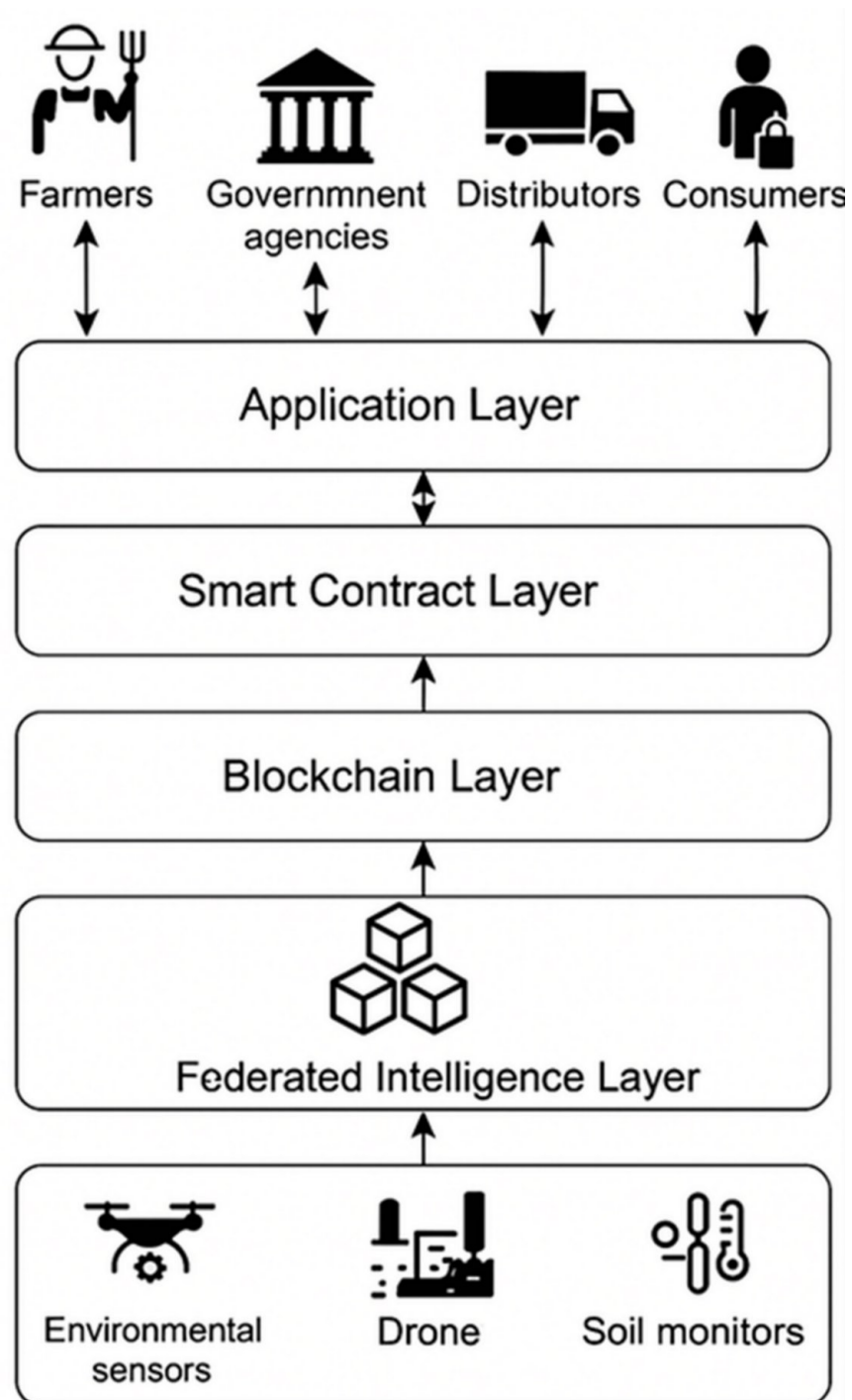


FIGURE 1: Architecture of AgriTrustChain++

In IoT edge layer, data acquisition and pre-processing are carried out, as shown in Figure 1. The first step in this process is the arrangement of IoT devices to monitor the health of the crop, sensors to measure moisture level of the soil, drones and weather stations in the agricultural fields. These devices help in sensing the environment continuously to monitor the parameters like pest activity, pH of the soil, humidity, and temperature that are related to crop. Redundant records, outliers and noise are eliminated using lightweight signal filtering procedures during pre-processing of raw data locally at the IoT edge layer. Transmission is carried out only after the standardization of values using normalization procedures. Due to this process, the utilization of bandwidth can be decreased and data integrity can be guaranteed at the higher level. Then, encryption process is applied to this pre-processed data and forwarded to edge computing units for performing analysis locally and train the model.

The decentralized intelligence can be enabled in the federated learning module. This helps in training the

machine learning models locally by the local servers or edge devices with their respective datasets. The predictions are generated by these devices based on the present and past readings of the sensors. Every edge node calculates the model parameters, gradient weights, etc., to a shared model instead of transporting complex data to a centralized cloud. Confidentiality is guaranteed by performing encryption on these model parameters and gradient weights utilizing secure aggregation procedures and then are transmitted to a global aggregator. These contributions are used to update the global model repeatedly and are reallocated back to all the contributing nodes. This technique reduces latency, preserves privacy of the data and also improves the model generalization. It is predominantly efficient in forecasting the yield, predicting the disease outbreak and detecting anomalies in heterogeneous farming environments.

Federated Aggregation:

$$w_{t+1} = \sum_{k=1}^K \frac{n_k}{n} w_t^k \quad \text{where } w_t^k \text{ is the model from node } k, \text{ and } n_k \text{ is its local dataset size.}$$

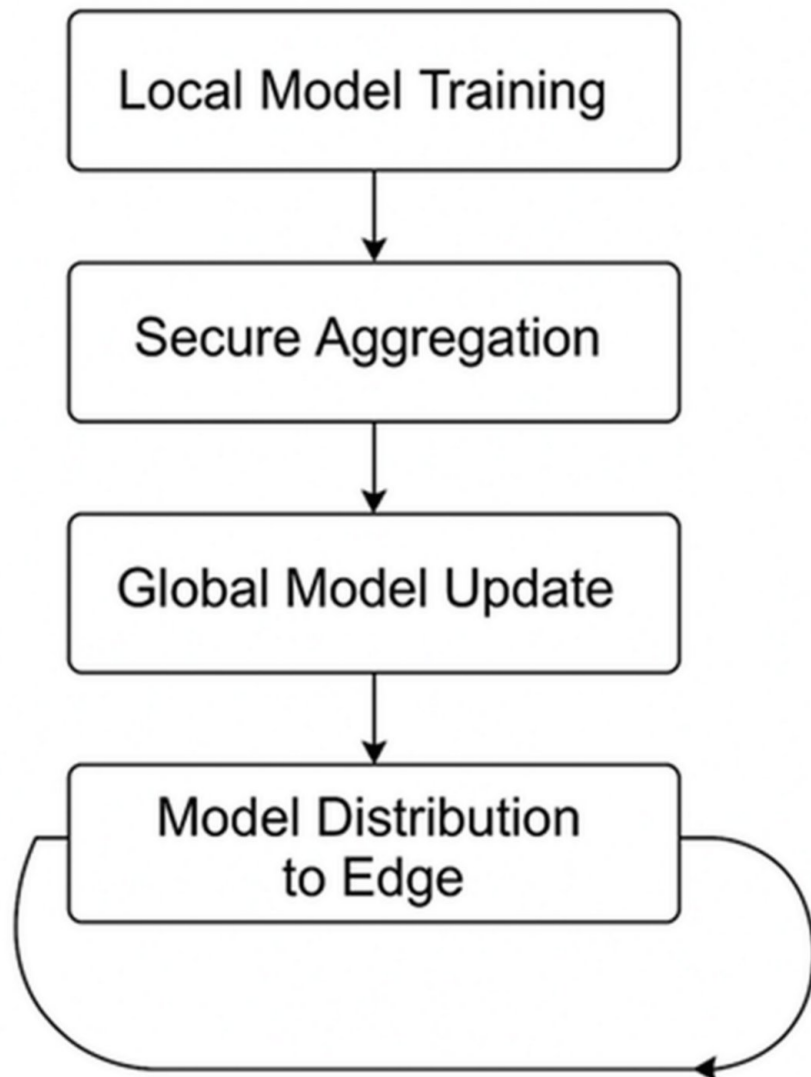


FIGURE 2: Create Same Image With 1,600 Pixels Wide

In the federated intelligence layer, as shown in Figure 2, a permissioned blockchain is used to permanently record each confirmed agricultural event, such as irrigation schedules, logistics updates, crop harvests, pesticide applications, etc., ensuring they cannot be altered. Smart contract rules and peer consensus are used to validate events before they are logged. Each event entry includes details such as event type, GPS coordinates, sensor source, and timestamp. After validation, the event data is hashed and appended to a new block on the ledger, guaranteeing it cannot be erased or changed. The blockchain structure provides regulatory transparency, distributor tracing, and verification tools for end users. This process enables auditability and end-to-end trust throughout the agricultural lifecycle.

Algorithm 1: Smart Traceability Contract

Input:

Sensor Data $S\#\#^d$ Timestamp $T\#\#^+$ BatchID $B\#\#^+$

Output:

Ledger entry recorded

Notification sent to logistics and regulator nodes

Begin

1. Validate inputs:

 $V = \text{ValidateInputs}(S, T, B)$

2. If validation fails:

3. If $V = 0 \Rightarrow \text{Reject}(S, T, B), \text{LogError}()$

then return.

4. Else, create transaction:

 $Tx \leftarrow \text{CreateTransaction}(S, T, B)$

5. Generate hash for the transaction:

 $TxHash = H(Tx)$ where $H(\cdot)$ is a secure hash function.

6. Form a new block:

 $\text{Block} \leftarrow \text{FormBlock}(TxHash, T, B)$

7. Verify block validity:

 $Vb = \text{VerifyBlock}(\text{Block})$

8. If block valid:

If $Vb = 1 \Rightarrow \text{Ledger} \cup \{\text{Block}\}, \text{NotifyNodes}(\{\text{Logistics}, \text{Regulator}\}, \text{Block})$

9. Else reject block:

 $\text{Reject}(\text{Block}), \text{ReportInconsistency}()$

10. End

Execution of predefined rules is carried out automatically by smart contracts, based on verified blockchain entries and sensor data. Alerts are triggered, insurance claims are initiated or further harvesting is blocked automatically if at least three independent edge nodes detect a disease or if safety thresholds for moisture levels are exceeded. Accountability and compliance are ensured by creating and deploying contracts through governance bodies or authorized regulatory authorities. Human intervention is minimized due to automation, which also helps prevent negligence or fraud and improves response times. Solidity is used to write these contracts, and consensus validation or real-time inputs are used to trigger them, as shown in Figure 3.

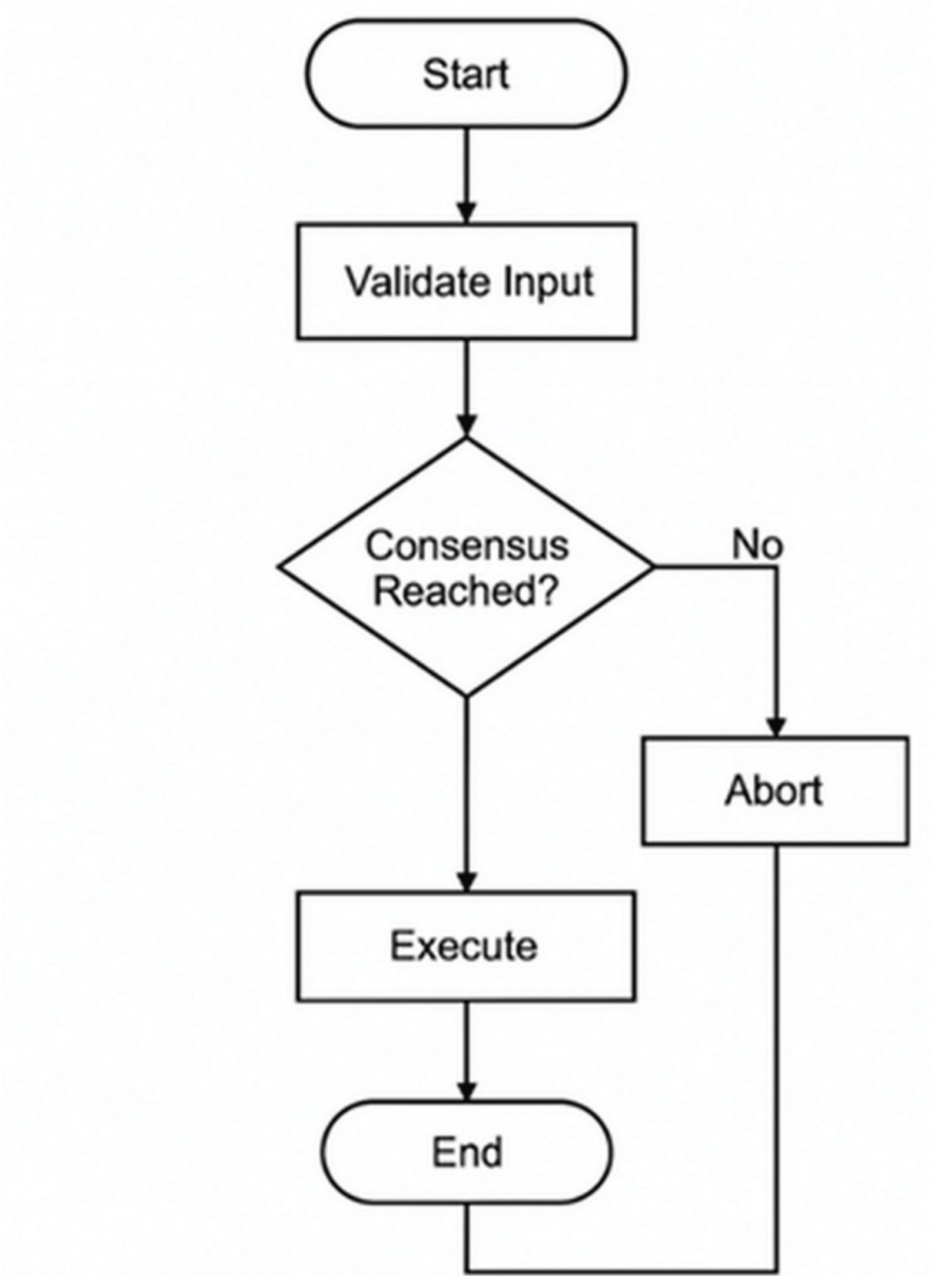


FIGURE 3: Smart Contract Execution Workflow

Multi-tiered security procedures are employed in AgriTrustChain++. Digital identity, along with role-based access control (RBAC), is assigned to every stakeholder, i.e., customers, government officials, distributors, and farmers. Due to RBAC, users can perform only specific actions based on their roles. For example, yield data is submitted by farmers, whereas transactions are verified and approved by regulators. Efficiency and confidentiality are guaranteed by lightweight cryptographic algorithms like AES-128 and ECC, which are used to encrypt both edge-to-chain and device-to-edge communications. AES-128 uses a block size of 128 bits and a key size of 128 bits; it is fast, secure, and used for encrypting payload data. ECC uses a 256-bit private key and a 512-bit public key; it is used for key exchange and digital signatures, providing strong security with low overhead. The blockchain consortium authority issues digital certificates for identity management, guaranteeing transaction non-repudiation and secure authentication. To guarantee the system is scalable and robust, the blockchain layer is constructed using a modular framework with channel-based transaction segregation. This allows transactions from various agencies, crops, or regions to be processed in parallel. Centralized data bottlenecks are reduced by federated learning, which fundamentally supports scalability. Additionally, fewer model updates and compression methods are used to reduce communication overhead. The RAFT consensus method is used because it is more scalable, efficient, and simpler to implement compared to Proof-of-Stake (PoS) and Proof-of-Work (PoW). To make the system feasible for deployment in rural or resource-limited areas,

smart contracts are optimized to execute automatically only when triggered by threshold conditions, thereby reducing needless computational overhead.

A privacy-preserving and decentralized framework, tailored for real-world deployment, guarantees intelligent agricultural practices, efficiency and security.

Results

Experimental evaluation

The simulation of the proposed system, AgriTrustChain++, was run 20 times to evaluate its effectiveness and feasibility. Edge-based federated learning agents, blockchain nodes and IoT sensors were included in the simulation system. The parameters used to measure the performance of the proposed system were scalability, model accuracy, energy consumption, latency and transaction throughput. Latency is defined as the total time taken from data collection to the completion of the transaction on the blockchain. Model accuracy measures how accurately the model predicts yield and classifies diseases. Energy consumption refers to the amount of power consumed by all nodes (edge devices and IoT sensors) in the system during peak activity. Scalability is defined as the extent to which the number of transactions, devices, and users can be increased. Finally, transaction throughput is the number of transactions processed per second. Fifteen farming cycles with different crop conditions, weather and soil types were considered for different trials of the experiment [28].

Experimental Setup

TensorFlow Federated, Hyperledger Fabric and Python are used for simulating the testing environment. Three virtual smart farms are considered, and GPS modules, soil moisture sensors and DHT11 for temperature/humidity are positioned. Raspberry Pi 4 Model B (4GB RAM, Quad-core Cortex-A72) is used to act as the local edge nodes. Real-time streaming of agricultural events like pest detection, irrigation, etc., is simulated in each farm. One ordering node and three peer nodes are used in the implementation of permissioned blockchain network, and Hyperledger Fabric v2.2 is used for Certificate Authority. In federated learning, disease of the crop is predicted using trivial Convolutional Neural Network model, and yield forecast is made using Long Short-Term Memory model. Simulation parameters and configuration are shown in Table 2. In this paper, RAFT is considered for the consensus protocol as it provides deterministic conclusiveness, simple operation, low latency and also avoids delay and high energy issues of PoW/PoS. To replicate the real-time farm constraints, the simulation parameters specified in Table 2 are considered. Scalability beyond 500 nodes is possible by dividing workloads via channels, installing multiple RAFT clusters, altering block sizes, optimizing chaincode and peer roles and leveraging lightweight state databases. The framework can support thousands of IoT devices with these optimizations.

Parameter	Value/Description
Edge Node Hardware	Raspberry Pi 4 (4GB RAM, 1.5GHz Quad-Core)
Blockchain Platform	Hyperledger Fabric v2.2
IoT Sensors	DHT11, Soil Moisture Sensor, GPS
Learning Framework	TensorFlow Federated
Local Model (Crop Disease)	Convolutional Neural Network (2 convolutional layers, 1 fully connected layer)
Local Model (Yield Forecast)	Long Short-Term Memory (2 layers, 50 units)
Data Transmission Protocol	Message Queuing Telemetry Transport over Transport Layer Security
Consensus Algorithm	Reliable, Replicated, Redundant and Fault-Tolerant (RAFT)
Simulation Duration	15 crop cycles

TABLE 2: Simulation Parameters and Configuration

Results and Analysis

The performance of the proposed system, AgriTrustChain++, is compared with AgriLedger and AgriFusion in terms of transaction throughput (transactions per second), scalability, energy consumption, accuracy of the model and transaction latency, and it is proved that the AgriTrustChain++ outperforms, as shown in

Table 3 and Figures 4-8. The reason for the improved performance is mainly because of the combination of latest technology like modular architecture, permissioned blockchain, privacy preserving federated learning and trivial cryptographic algorithms that are designed for IoT-based smart agriculture.

Metric	AgriFusion	AgriLedger	AgriTrustChain++
Latency (s)	3.4	2.9	1.8
Accuracy (%)	83	86	92
Relative Score	3.0	2.0	1.0
Scalability	200	300	500
Throughput	85	90	110

TABLE 3: Comparison Table

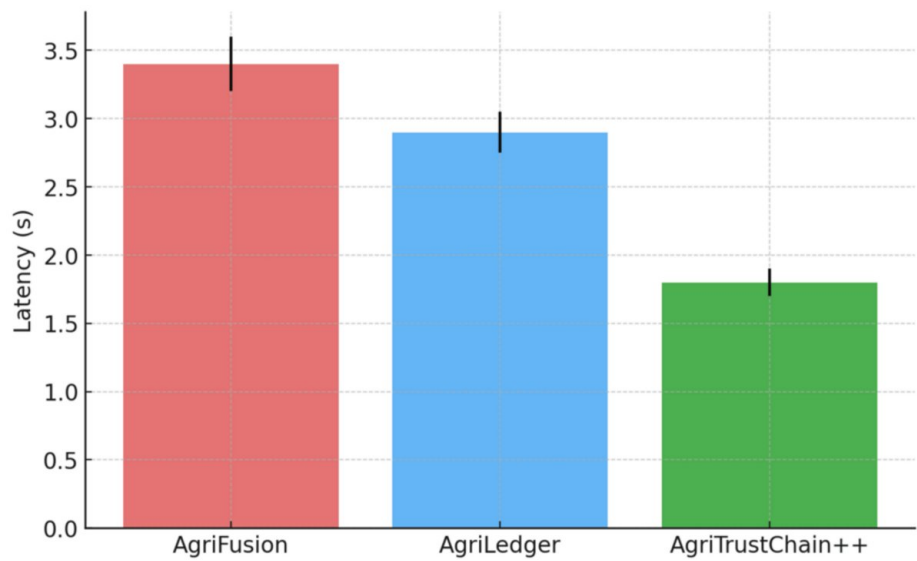


FIGURE 4: Transaction Latency

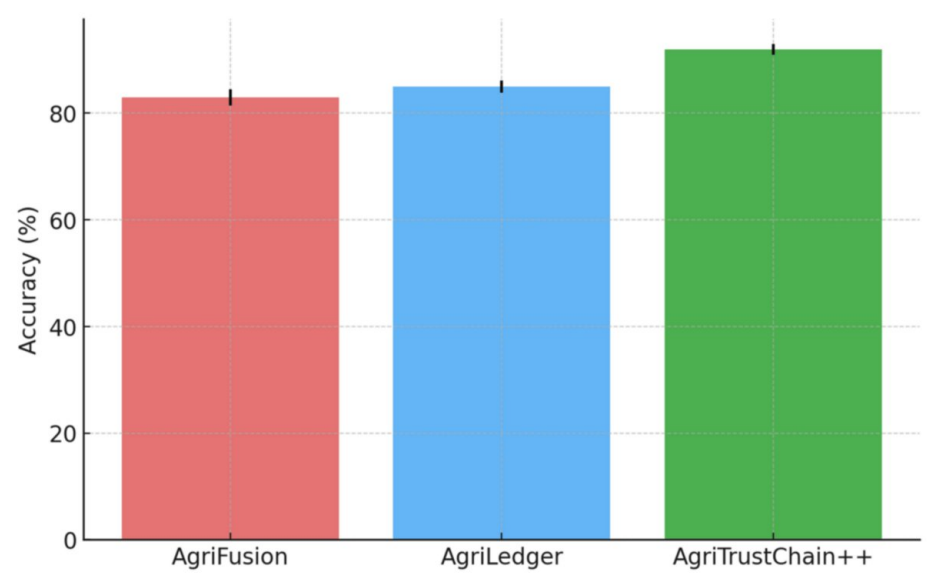


FIGURE 5: Accuracy

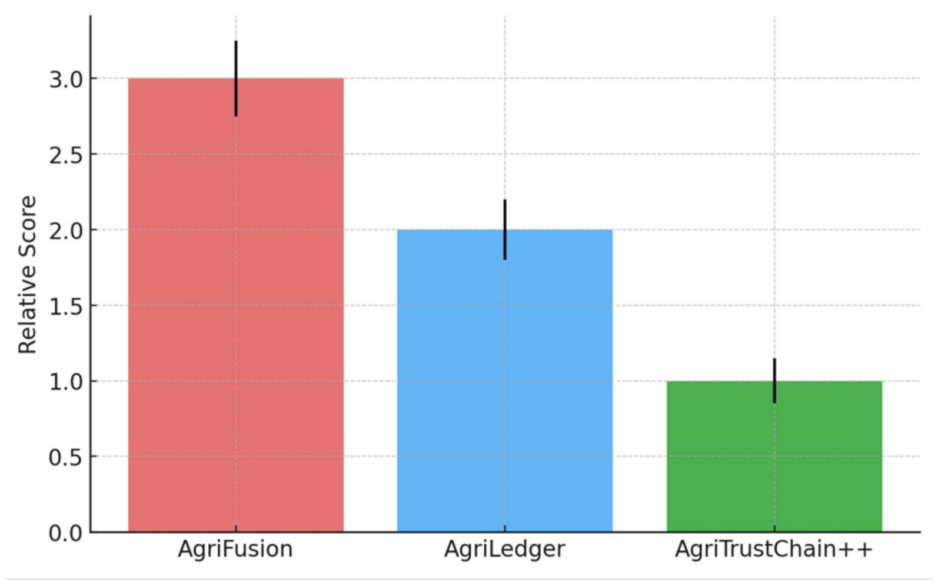


FIGURE 6: Energy Consumption (Relative Scale; Lower Is Better)

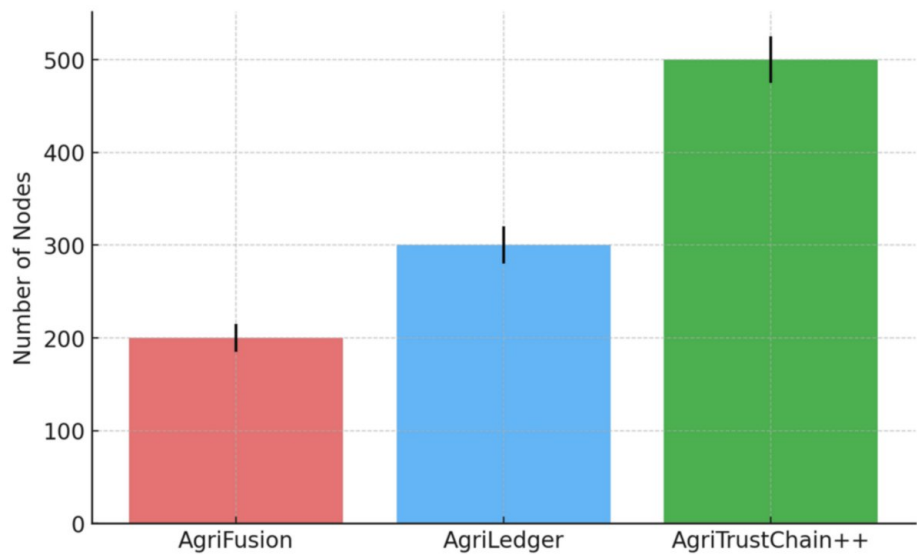


FIGURE 7: Scalability (Supported IoT Nodes)

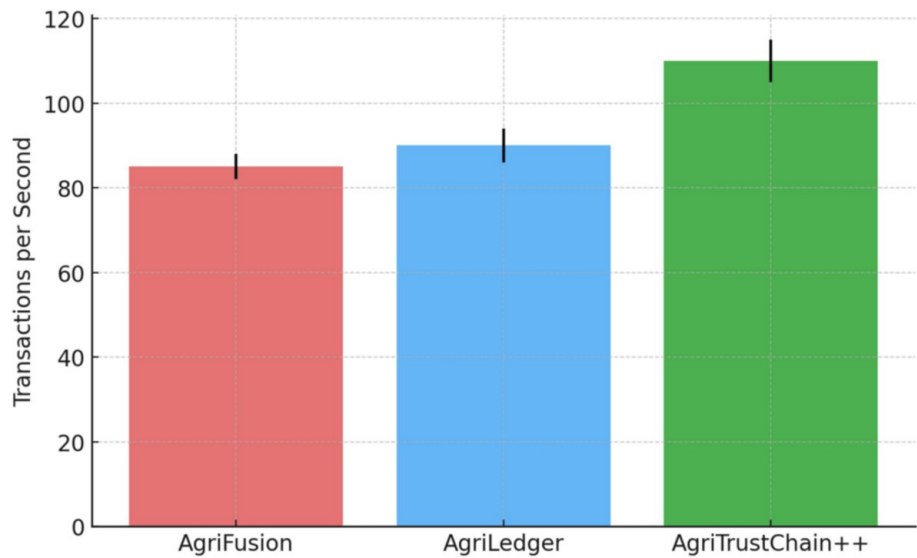


FIGURE 8: Transaction Throughput (Transactions per Second)

Discussion

As RAFT is used as consensus algorithm in the permissioned blockchain, low transaction latency is attained by the proposed algorithm, AgriTrustChain++. RAFT permits quicker agreement amongst a restricted number of authorized nodes, whereas traditional public blockchain systems depend on PoW, which consume more power, or PoS, which is slower. The processing delays are reduced due to the complexity and quantity of data that is transmitted is reduced as the pre-processing of data is taken at the edge layer. This task also guarantees the real-time reaction for important tasks like disease alerts and irrigation control.

The federal learning plays a key role in the improvement of model accuracy, achieving disease detection up to 92.5%. It allows edge devices to train local machine learning models on-site using actual farm-level data. To maintain user privacy and enrich the global model with various data inputs from dissimilar farming conditions, AgriTrustChain++ shares only model updates but not raw data. This produces a robust model with extensive application that outperforms centralized alternatives that abide limited, homogeneous training data.

In rural and resource-constrained environments, AgriTrustChain++ promotes deployment of energy

efficiency. Power consumption is minimized by the system through various techniques: (i) local computation at edge nodes prevents the call for continuous high-bandwidth cloud connectivity, (ii) only under well-defined conditions, smart contracts are triggered and arrest unnecessary processing, and (iii) avoiding heavy computational demands, lightweight cryptographic algorithms such as ECC establishes secure data exchange.

With the use of channel-based blockchain architecture in Hyperledger Fabric, where transactions are shielded and executed simultaneously across different channels, the framework become highly scalable. It supports more than 500 concurrent IoT nodes without degradation in performance. Furthermore, to avoid the central server bottlenecks typically encountered in traditional systems, the training load is distributed by federated learning architecture.

Finally, AgriTrustChain++ accomplishes a high transaction throughput of 110 transactions per second using the efficient design of smart contracts. They are written to execute necessary operations and the streamlined event logging mechanism that batches non-crucial updates. Large volumes of agricultural data can be securely and rapidly processed using hybrid approach of the system, i.e., to unite the automation by smart contracts and modular storage via distributed ledgers. Owing to this, the system becomes suitable to promote real-time applications like supply chain tracking, compliance auditing and subsidy management.

In summary, the careful architectural integration of edge intelligence, permissioned blockchain protocols, smart automation, and scalable data pipelines together led to the superior performance of AgriTrustChain++. All these features make it a dominant and practical framework for future ready, data-driven agriculture.

Threat analysis

The proposed framework has numerous potential threats typical in IoT-blockchain agricultural systems. Data integrity attacks like tampering or injection of false sensor readings can deceive decision-making if not properly authenticated. Privacy threats arise from unauthorized access to sensitive farm data, particularly if raw information is exposed at the time of transmission or training. Denial-of-Service attacks could target IoT gateways or blockchain nodes, troubling real-time operations. Sybil and consensus operation attacks tend to pose risks to blockchain integrity if opponents attempt to create fake identities or compromise nodes. Model poisoning attacks in federated learning impend system accuracy by presenting corrupted updates. Lastly, resource exhaustion is a concern, as IoT devices have limited storage and power, making them susceptible to battery-draining or storage-flooding activities.

Mitigation in the proposed system comprises lightweight encryption, role-based access control, RAFT consensus and federated learning with update validation, guaranteeing security, scalability and flexibility in contrast to these threats.

Conclusions

This paper proposed AgriTrustChain++. It is a hybrid framework that integrates federated edge intelligence, permissioned blockchain and lightweight smart contracts to deliver secure, scalable and intelligent automation in smart agriculture systems. The framework is proven to be effectively outperforming in terms of transaction latency, model accuracy, throughput, energy consumption and scalability after precise experimentation and simulation. Data privacy is preserved simultaneously enabling robust predictive modeling by choosing federated learning. Smooth real-time operations, even under high load, are ensured by modular blockchain channels and organized consensus mechanisms. Hyperledger and Tensorflow federated are used in the implementation. Over 15 crop cycles data of around 3,000 records (synthetic dataset) generated by IoT and edge devices in the simulation process are used. The performance of the proposed framework is evaluated in terms of throughput, energy conservation, accuracy and average latency and is compared with AgriFusion and AgriLedger. The graphs shown prove that the proposed framework AgriTrustChain++ outperforms with 110 records/s of throughput, 27% energy conservation, 92.5% accuracy and 1.8 s average latency.

Work in the future will aim to enhance fault tolerance, extending the framework to aid multi-modal data sources like satellite imagery and unmanned aerial vehicle-based imaging, and incorporating adaptive learning for edge devices under dynamic conditions. Additional performance evaluation under distinct climatic zones and network topologies is also suggested.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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References

1. Torky M, Hassanein AE: Integrating blockchain and the internet of things in precision agriculture: Analysis, opportunities, and challenges. *Computers and Electronics in Agriculture*. 2020, 178:105476. [10.1016/j.compag.2020.105476](https://doi.org/10.1016/j.compag.2020.105476)
2. Lamtzidis O, Pettas D, Gialelis J: A novel combination of distributed ledger technologies on internet of things: Use case on precision agriculture. *Applied System Innovation*. 2019, 2:30. [10.3390/asi2030030](https://doi.org/10.3390/asi2030030)
3. Liu W, Shao XF, Wu CH, Qiao P: A systematic literature review on applications of information and communication technologies and blockchain technologies for precision agriculture development. *Journal of Cleaner Production*. 2021, 298:126763. [10.1016/j.jclepro.2021.126763](https://doi.org/10.1016/j.jclepro.2021.126763)
4. Pradeep G, Ramamoorthy S, Krishnamurthy M, Rajakumar PS, Saritha V: Hybrid Energy-Efficient Task Offloading Algorithm (HEETA): A framework for optimizing edge computing offloading decisions. *Journal of Electrical Systems*. 2024, 20:92-111. [10.52783/jes.1835](https://doi.org/10.52783/jes.1835)
5. Pradeep G, Ramamoorthy S, Krishnamurthy M, Saritha V: Energy prediction and task optimization for efficient IoT task offloading and management. *International Journal of Intelligent Systems and Applications in Engineering*. 2023, 12:411-427.
6. Lin W, Huang X, Fang H, et al.: Blockchain technology in current agricultural systems: from techniques to applications. *IEEE Access*. 2020, 8:143920-143937. [10.1109/access.2020.3014522](https://doi.org/10.1109/access.2020.3014522)
7. Dey K, Shekhawat U: Blockchain for sustainable e-agriculture: Literature review, architecture for data management, and implications. *Journal of Cleaner Production*. 2021, 316:128254. [10.1016/j.jclepro.2021.128254](https://doi.org/10.1016/j.jclepro.2021.128254)
8. Chaganti R, Varadarajan V, Gorantla VS, Gadekallu TR, Ravi V: Blockchain-based cloud-enabled security monitoring using internet of things in smart agriculture. *Future Internet*. 2022, 14:250. [10.3390/fi14090250](https://doi.org/10.3390/fi14090250)
9. Hang L, Ullah I, Kim DH: A secure fish farm platform based on blockchain for agriculture data integrity. *Computers and Electronics in Agriculture*. 2020, 170:105251. [10.1016/j.compag.2020.105251](https://doi.org/10.1016/j.compag.2020.105251)
10. Pincheira M, Vecchio M, Gialfreda R: Characterization and costs of integrating blockchain and IoT for agri-food traceability systems. *Systems*. 2022, 10:57. [10.3390/systems10030057](https://doi.org/10.3390/systems10030057)
11. Li W, Wang X, Han S: Coverage enhance in boundary deployed camera sensor networks for airport surface surveillance. *IEEE Access*. 2021, 9:145728-145738. [10.1109/access.2021.3116113](https://doi.org/10.1109/access.2021.3116113)
12. Babar AZ, Akan OB: Sustainable and precision agriculture with the internet of everything (IoE). *arXiv*. 2024, [10.48550/arXiv.2404.06341](https://arxiv.org/abs/2404.06341)
13. Amraouy O, Boukhali Y, Bouazi A, Kabbaj MN, Benbrahim M: Blockchain-based IoT for precision agriculture: Applications, research challenges, and future directions. *Enhancing Performance, Efficiency, and Security Through Complex Systems Control*. Chana I, Bouazi A, Ben-azza H (ed): IGI Global Scientific Publishing, Hershey, PA; 2024. 147-174. [10.4018/979-8-3693-0497-6.ch010](https://doi.org/10.4018/979-8-3693-0497-6.ch010)
14. Hu S, Huang S, Huang J, Su J: Blockchain and edge computing technology enabling organic agricultural supply chain: A framework solution to trust crisis. *Computers & Industrial Engineering*. 2021, 153:107079. [10.1016/j.cie.2020.107079](https://doi.org/10.1016/j.cie.2020.107079)
15. Kharche A, Badholia S, Upadhyay RK: Implementation of blockchain technology in integrated IoT networks for constructing scalable ITS systems in India. *Blockchain Research and Applications*. 2024, 5:100188. [10.1016/j.bcr.2024.100188](https://doi.org/10.1016/j.bcr.2024.100188)
16. Khan AA, Shaikh ZA, Belinskaja L, et al.: A blockchain and metaheuristic-enabled distributed architecture for smart agricultural analysis and ledger preservation solution: A collaborative approach. *Applied Sciences*. 2022, 12:1487. [10.3390/app12031487](https://doi.org/10.3390/app12031487)
17. Demestichas K, Daskalakis E: Data lifecycle management in precision agriculture supported by information and communication technology. *Agronomy*. 2020, 10:1648. [10.3390/agronomy10111648](https://doi.org/10.3390/agronomy10111648)
18. Patel DH, Shah KP, Gupta R, et al.: Blockchain-based crop recommendation system for precision farming in IoT environment. *Agronomy*. 2023, 13:2642. [10.3390/agronomy13102642](https://doi.org/10.3390/agronomy13102642)
19. Wu X: Dynamic evaluation of college English writing ability based on AI technology. *Journal of Intelligent Systems*. 2022, 31:298-309. [10.1515/jisys-2022-0020](https://doi.org/10.1515/jisys-2022-0020)
20. Saba T, Rehman A, Haseeb K, Bahaj SA, Lloret J: Trust-based decentralized blockchain system with machine

- learning using Internet of agriculture things. Computers & Electrical Engineering. 2023, 108:108674. [10.1016/j.compeleceng.2023.108674](https://doi.org/10.1016/j.compeleceng.2023.108674)
21. Adeboye OB, Schultz B, Adeboye AP, Adekalu KO, Osunbitan JA: Application of the AquaCrop model in decision support for optimization of nitrogen fertilizer and water productivity of soybeans. Information Processing in Agriculture. 2021, 8:419-436. [10.1016/j.inpa.2020.10.002](https://doi.org/10.1016/j.inpa.2020.10.002)
22. Awan S, Ahmed S, Ullah F: IoT with blockchain: A futuristic approach in agriculture and food supply chain. Wireless Communications and Mobile Computing. 2021, 2021:5580179. [10.1155/2021/5580179](https://doi.org/10.1155/2021/5580179)
23. Cao Y, Yi C, Wan G, Hu H, Li Q, Wang S: An analysis on the role of blockchain-based platforms in agricultural supply chains. Transportation Research Part E: Logistics and Transportation Review. 2022, 163:102731. [10.1016/j.tre.2022.102731](https://doi.org/10.1016/j.tre.2022.102731)
24. Krishna PV, Sivanesan S, Misra S, Obaidat MS: Learning automaton-based context oriented middleware architecture for precision agriculture. 2015 International Conference on Computer, Information and Telecommunication Systems (CITS), Gijon, Spain. 2015, 1-5. [10.1109/CITS.2015.7297720](https://doi.org/10.1109/CITS.2015.7297720)
25. Mahalingam N, Sharma P: An intelligent blockchain technology for securing an IoT-based agriculture monitoring system. Multimedia Tools and Applications. 2024, 83:10297-10320. [10.1007/s11042-023-15985-8](https://doi.org/10.1007/s11042-023-15985-8)
26. Rahman W, Hossain MM, Hasan M, Iqbal MS, Rahman M, Hasan KF, Moni MA: Automated detection of harmful insects in agriculture: A smart framework leveraging IoT, machine learning, and blockchain. IEEE Transactions on Artificial Intelligence. 2024, 5:4787-4798. [10.1109/tai.2024.3394799](https://doi.org/10.1109/tai.2024.3394799)
27. Sharma I, Khullar V: Blockchain-enabled federated learning-based privacy preservation framework for secure IoT in precision agriculture. Journal of Industrial Information Integration. 2025, 44:100765. [10.1016/j.jii.2024.100765](https://doi.org/10.1016/j.jii.2024.100765)
28. Synthetic IoT crop monitoring dataset. (2025). Accessed: March 5, 2025; <https://drive.google.com/file/d/1WMo6pNzqSrRt7np4IOYNVHgsue5cLgRN/view?usp=sharing>.