RESEARCH ARTICLE

AgriChainSync: A Scalable and Secure Blockchain-Enabled Framework for IoT-Driven Precision Agriculture

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ABSTRACT The rapid advancement of precision farming, automated irrigation systems, and predictive analytics has revolutionized agriculture, but these innovations also introduce new challenges, particularly in data integrity and security. With the increased usage of IoT devices, data integration of vast amounts of data becomes critical. This paper proposes a comprehensive framework, AgriChainSynch, which integrates IoT, blockchain, and artificial intelligence systems to address these challenges. The proposed framework shows a dynamic data storage algorithm that optimizes storage decisions based on data characteristics and features. Furthermore, the Blockchain Integration Layer (BIL) ensures security and scalability with a Feedback and Adaptation Module (FAM) that continuously improves systems performance. The proposed hybrid blockchain structure balances privacy and scalability with homomorphic encryption. Extensive experimentation and validation demonstrate that the proposed framework improves storage efficiency with reduced processing time and enhances network performance, offering improved solutions for modern agricultural systems. The findings underscore the potential of integrating IoT, blockchain, and AI under one umbrella, supporting large-scale farming operations.

INDEX TERMS Blockchain, IA, intelligent framework, AI, IoT.

I. INTRODUCTION

Agriculture has seen substantial transformation with the advent of digital technologies, particularly through the integration of the Internet of Things (IoT). This development has led to the rise of Intelligent Agriculture (IA), a system that utilizes real-time monitoring, automation, and data-driven decision-making to enhance farming practices [1], [2], [3], [4], [5]. However, alongside these benefits, the

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implementation of such technologies has introduced several challenges that need careful consideration.

Initially, blockchain technology was embraced as a promising tool to complement Intelligent Agriculture (IA), offering secure, transparent, and decentralized methods for recording agricultural transactions [6], [7].

Blockchain technology initially appeared to be an ideal solution for enhancing traceability and trust within agricultural supply chains. Its decentralized and transparent nature promised to address many of the existing challenges in ensuring the integrity of agricultural transactions [8], [9].

However, as the adoption of IoT devices increased and the volume of data generated by these devices grew, several new challenges emerged [10]. Managing large volumes of data, maintaining fast execution speed, and maintaining adequate storage capacity became increasingly difficult [11]. Moreover, scalability emerged as a critical issue, with traditional blockchain systems proving inadequate in meeting the demands of an expanding IA infrastructure without compromising overall system performance [12].

Another critical challenge lies in the diverse nature of agriculture itself. Agricultural practices vary widely depending on region, climate, and local customs [4]. The dynamic nature of agricultural parameters poses significant challenges in developing a universal IA system that can be effectively applied across diverse contexts. Each farming environment has its own set of unique requirements, influenced by factors such as climate, soil conditions, crop types, and local practices. Consequently, IA systems must be designed with a high degree of flexibility, allowing them to adapt to these varying needs. Creating such adaptable systems demands meticulous design and a focus on customization, ensuring that solutions can be tailored to meet the specific demands of different agricultural contexts. This approach is essential for the successful implementation of IA technologies in a wide range of farming environments [13], [14].

Moreover, agriculture is a field that is constantly evolving. Factors such as changing weather patterns, pest outbreaks, market fluctuations, and new regulations mean that an IA system must be capable of real-time adaptation. A system that cannot quickly respond to these changes risks becoming obsolete or less effective over time. Therefore, IA solutions must include mechanisms for continuous learning and updating to remain relevant and useful in the face of ongoing changes [15].

Despite the potential benefits of integrating technologies like blockchain and AI into agriculture, many farmers and stakeholders find these innovations complex and difficult to use [16]. To make these technologies effective, IA solutions must be designed to be user-friendly and accessible. This involves creating interfaces that are easy to navigate and providing clear, straightforward instructions. Ensuring these technologies are accessible to both tech-savvy users and those with less experience is key to achieving widespread adoption.

Adoption of IA technologies is also uneven across different regions. Factors such as infrastructure limitations, economic disparities, and lack of awareness contribute to this variation. In many areas, farmers do not have access to the necessary technology or are unaware of the benefits that IA can offer [17]. Addressing these inequalities is a significant challenge, as it involves not only developing technological solutions but also increasing awareness and building the necessary infrastructure to support IA [18].

The integration of IoT, blockchain, and AI technologies in agriculture holds great promise, offering the potential for more efficient, sustainable, and secure farming practices. However, the challenges associated with data management,

system scalability, adaptability to diverse agricultural contexts, and user accessibility must be addressed to fully realize this potential. By tackling these issues, IA can become a transformative force in agriculture, paving the way for a more resilient and responsive agricultural system.

The proposed framework is well-suited for the complex structure of Intelligent Agriculture (IA) by utilizing a combination of IoT, blockchain, and AI technologies to manage heterogeneous data streams. The framework effectively handles the diverse data types generated from IA systems such as sensor data, drone imagery, and satellite readings through a dynamic data storage mechanism coupled with entropy-based Markov Decision Processes (MDPs) that optimize data routing and storage. This ensures efficient, decentralized data processing and secure storage across large-scale agricultural operations.

To address the temporal complexities inherent in IA, Recurrent Neural Networks (RNNs) are employed for time-dependent data, such as soil moisture trends and irrigation schedules, enhancing predictive analytics and enabling adaptive decision-making. The framework's scalability is demonstrated through its capacity to manage varying data loads from small to large-scale farm operations—without compromising latency or throughput, ensuring operational stability. Additionally, the integration of homomorphic encryption techniques guarantees data privacy and integrity, a critical concern in decentralized agriculture systems.

By optimizing both security and performance, AgriChainSync provides a robust, scalable solution for the dynamic, data-intensive environment of Intelligent Agriculture, ensuring its suitability for real-world applications.

The remaining paper is organized as follows: Section II contains review of related work. Contribution of our work is discussed in Section III. Furthermore, Section IV consists of proposed framework. Experimental settings are part of Section V. Similarly, Section VI contains results & discussion, and Section VII concludes the study.

II. RELATED WORK

The integration of the Internet of Things (IoT) in agriculture has led to a significant shift from traditional, labor-intensive methods to data-driven operations [19]. IoT devices enable real-time monitoring and decision-making, improving the efficiency and productivity of farming. These devices track key factors like soil conditions, crop growth, irrigation, and weather, supporting precision farming that optimizes resources and maximizes yields. However, this technological progress also brings challenges, particularly in managing, securing, and maintaining the integrity of the large volumes of data generated.

The widespread use of IoT devices in agriculture produces vast amounts of data, including metrics like soil moisture, crop health, and livestock management. This data is essential for informed decision-making in modern farming. However, the volume and complexity of this data pose significant challenges in management [30]. Traditional systems often

TABLE 1. Systematic comparison of existing techniques with proposed framework.

Paper Citation	IoT-based Agriculture	DL Integration	Pest Detection	Blockchain Security	AI Analytics	Env. Monitoring	Load Balancing	Low Latency/Energy
[20]	✓	✗	✗	✗	✓	✓	✗	✗
[21]	✓	✗	✗	✗	✓	✗	✓	✓
[22]	✓	✓	✗	✗	✓	✓	✗	✗
[23]	✓	✓	✓	✗	✓	✓	✗	✓
[24]	✗	✗	✗	✓	✗	✗	✗	✗
[25]	✓	✓	✗	✓	✗	✓	✗	✓
[26]	✓	✗	✗	✓	✓	✓	✗	✗
[27]	✓	✓	✓	✗	✓	✓	✗	✓
[28]	✗	✗	✗	✓	✓	✗	✗	✗
[29]	✓	✗	✗	✓	✗	✓	✗	✗
Proposed Framework	✓	✓	✓	✓	✓	✓	✓	✓

struggle to handle the large and varied data generated by IoT devices, raising concerns about data integrity, security, and reliability factors that are crucial for accurate agricultural decisions.

To address these challenges, blockchain technology has emerged as a promising solution for enhancing data security in IoT-enabled agricultural systems. Blockchain's decentralized architecture provides a strong framework for securely storing and managing data, ensuring transparency. This is substantial in agriculture, where data accuracy and trustworthiness are critical. For example, blockchain can establish a permanent, verifiable record of transactions related to crop yields, livestock management, and resource usage, accessible to all stakeholders in the agricultural supply chain. However, despite its potential, integrating blockchain presents its own challenges, particularly in terms of scalability [31].

Scalability is one of the most significant challenges in implementing blockchain technology in agriculture [32]. As the number of IoT devices on a farm increases, the volume of data that needs to be processed and stored on the blockchain escalates. This growth in data volume can lead to performance issues, including slower data processing speeds, limited storage capacity, and reduced overall system efficiency. Blockchain networks must scale effectively to accommodate the growing data demands without compromising performance. This scalability challenge is a critical barrier to the widespread adoption of blockchain in agriculture, as existing systems often struggle to manage the large-scale IoT deployments characteristic of modern farming.

The diversity of agricultural practices across different regions further complicates the integration of IoT and blockchain technologies. Agricultural systems vary significantly depending on regional factors such as climate, soil types, crop varieties, and farming practices [33]. Implementing a one-size-fits-all IoT-blockchain solution is impractical because each agricultural context has its own unique requirements and challenges. Effective IoT-blockchain systems need to prioritize adaptability and interoperability, ensuring they can seamlessly integrate with diverse agricultural setups without requiring extensive modifications to existing practices.

Moreover, agriculture is inherently dynamic, with constant changes driven by factors such as weather variability, pest outbreaks, market fluctuations, and evolving regulatory requirements. A rigid IoT-blockchain system would quickly become outdated and ineffective in such a fluid environment. Therefore, a successful system must incorporate mechanisms for real-time adaptation and continuous improvement based on field feedback. This adaptability is essential for ensuring the long-term viability and effectiveness of IoT-blockchain systems in agriculture.

Another significant challenge is the complexity and usability of IoT-blockchain systems. While these technologies hold great potential, their complexity can be overwhelming for many farmers and agricultural stakeholders, particularly those at the grassroots level [34]. The successful adoption of IoT-blockchain solutions requires designing user-friendly interfaces and providing clear, accessible explanations to bridge the gap between technological capabilities and user understanding. Ensuring that these technologies are accessible to a broad range of users, from tech-savvy innovators to traditional farmers, is essential for their widespread adoption and success [35].

The integration of artificial intelligence (AI) with IoT and blockchain systems in agriculture is another area of growing interest [36]. AI has the potential to significantly enhance decision-making processes by analyzing complex data patterns and predicting agricultural outcomes [37]. By incorporating machine learning algorithms, AI can optimize resource allocation, improve crop management practices, and increase overall farm efficiency. However, the integration of AI with blockchain and IoT introduces new challenges, such as ensuring the transparency and interpretability of AI-driven decisions within a decentralized network [38]. The convergence of these technologies is still in its early stages, with many aspects requiring further research and development to realize their full potential.

Smart contracts, which automate various agricultural processes within blockchain networks, offer a promising application of blockchain technology in agriculture. These contracts can automate tasks like supply chain management, transaction processing, and compliance monitoring, reducing

the need for manual oversight and decreasing the risk of fraud. However, the complexity involved in coding, deploying, and maintaining smart contracts, especially in diverse agricultural environments, poses a significant challenge to their widespread adoption. Developing user-friendly platforms that simplify the deployment and management of smart contracts is crucial for overcoming this challenge and unlocking the full potential of blockchain in agriculture [39], [40], [41].

Finally, data interoperability between different IoT, AI and blockchain systems is a crucial challenge that must be addressed to ensure the seamless integration and utilization of heterogeneous data across agricultural systems [42], [43]. Standardizing data formats and communication protocols is essential for enabling IoT devices and blockchain networks to interact effectively. However, achieving such standardization is challenging, particularly across diverse agricultural systems with varying levels of technological adoption and infrastructure development. Overcoming these challenges requires coordinated efforts to develop and implement standards that can be widely adopted across the agricultural sector.

The integration of IoT, blockchain, and AI in agriculture holds significant promise but is challenged by issues like scalability, data management, user accessibility, energy efficiency, smart contract complexity, and data interoperability. Addressing these challenges requires robust frameworks that combine multiple technologies under a unified approach, along with collaboration among technology developers, policymakers, and agricultural stakeholders. By overcoming these hurdles, we can fully unlock the potential of digital agriculture and ensure its benefits are shared globally and equitably.

Table 1 above presents a comprehensive comparison of various existing frameworks and the proposed Agrisynch system across several key features relevant to precision agriculture. The evaluated systems vary in terms of their support for IoT-based precision agriculture, deep learning (DL) integration, pest detection, blockchain for security, AI-driven predictive analytics, environmental monitoring, load balancing, and energy efficiency.

While some of the papers address individual components such as IoT-based precision agriculture or blockchain security, they often lack comprehensive integration. Notably, few systems like AgriSegNet and AIoT-based frameworks incorporate deep learning and environmental monitoring but lack a focus on blockchain security or low-latency operations.

In contrast, proposed framework demonstrates a holistic approach by integrating all critical features, including IoT, deep learning, blockchain security, and predictive analytics, providing a more robust and scalable solution for precision agriculture. This makes Agrisynch a superior framework compared to the existing works, as it covers a broader spectrum of functionalities essential for modern smart farming systems.

III. MOTIVATION AND CONTRIBUTIONS

Considering all aforementioned factors observed in literature review, this paper aims to address these challenges in-depth by proposing following contributions:

1) The first major contribution is to develop dynamic data storage optimization algorithm for agricultural blockchain systems. This algorithm efficiently manages large, diverse datasets by using Bayesian classifiers, decision trees, and gradient descent to dynamically categorize data. It determines whether to store full transactions or hashes based on real-time data attributes like size, frequency, and importance. This method enhances storage efficiency, reduces system overload, and maintains data integrity, addressing key scalability and storage challenges in IoT-driven agriculture.

2) The second major contribution is the AgriChainSync protocol, a communication framework for real-time data processing, synchronization, and network optimization in agricultural blockchain systems. It utilizes edge computing, dynamic programming for routing, and differential equations for synchronization. By tackling network latency, data coherence, and load balancing, AgriChainSync ensures efficient and timely data transmission. This protocol addresses critical challenges in real-time processing and network performance for IoT-enabled agriculture.

3) The third contribution is the development of a hybrid blockchain framework that integrates permissioned and permissionless structures to balance privacy, transparency, and scalability in agricultural data management. The framework uses entropy-based Markov Decision Processes (MDPs) for optimal routing, homomorphic encryption for security, and neural networks for adaptive data processing. It also features a predictive feedback loop with recurrent neural networks (RNNs) to adapt to changing network conditions. RNNs are ideal for AgriChainSync as they effectively model time-dependent data like weather trends and irrigation schedules, which are crucial in agriculture. While CNNs handle spatial data better, the temporal nature of agricultural processes makes RNNs more suitable for capturing evolving patterns, enabling accurate predictions and improved real-time decision-making. [44] This solution effectively addresses scalability and security challenges in agricultural blockchain systems, ensuring high throughput and data privacy while managing diverse and complex datasets.

IV. PROPOSED METHODOLOGY

The proposed methodology for developing an optimized IoT-enabled agricultural blockchain system consists of several key components, each aimed at addressing the specific challenges of efficiency, scalability, and interoperability.

Figure 1 demonstrates the proposed framework where distributed edge computing is central to managing data

efficiently in precision agriculture. The system processes data at the edge, close to IoT devices, reducing latency and bandwidth usage, and enabling real-time decision-making across multiple nodes.

The Data Characterization Module (DCM) preprocesses and categorizes data locally using machine learning, minimizing the transmission of raw data to the central system. This is paired with the Smart Data Engine (SDE), which optimizes data for storage and transmission through aggregation and compression. By handling these tasks at the edge, the system reduces network congestion and ensures data integrity.

AgriSync manages the flow of data, optimizing routing across the network based on urgency and conditions, minimizing delays. The Blockchain Integration Layer (BIL) ensures data security and integrity by validating transactions in a decentralized ledger, without relying on a central server.

Finally, the Feedback and Adaptation Module (FAM) dynamically adjusts processing strategies using real-time feedback, ensuring efficient load distribution across the edge nodes. Together, these components enable distributed edge computing, allowing the system to handle complex, large-scale agricultural data efficiently and securely, while ensuring real-time operations and scalability.

A. DYNAMIC DATA STORAGE

The proposed framework to develop a dynamic, optimized algorithm for data storage in agricultural blockchain systems addresses the critical issue of managing large datasets with multiple features. The proposed framework in this study integrated a sophisticated mathematical model with advanced algorithms and blockchain protocols to develop a system that automatically and dynamically adjusts and chooses between storing complete data and hashed based on data feature and characteristics, which includes size, frequency and priority.

The first component of the proposed framework is the Data Characterization Module (DCM).

The proposed framework is designed to handle diverse agricultural data types, including structured (e.g., soil moisture, temperature), unstructured (e.g., weather forecasts, image data), and semi-structured data (sensor logs). To address this, the framework incorporates a Data Characterization Module (DCM) that uses a combination of Bayesian classifiers and decision trees to analyze incoming data types, allowing it to categorize data into appropriate formats before storage. Image data, for instance, can be compressed and stored as metadata within the blockchain, while sensor data can be processed in real-time and added as structured data points. These optimizations improve both storage and retrieval efficiency, ensuring seamless integration across all data types.

DCM analyses incoming agricultural data from parameters ranging from soil moisture levels to crop growth metrics and livestock health indicators. DCM contains Bayesian classifiers to analyze the data for multivariate analysis.

Mathematical analysis can be observed as follows:

$$P(C \mid x_1, x_2, \ldots, x_n) = \frac{P(x_1, x_2, \ldots, x_n \mid C)P(C)}{P(x_1, x_2, \ldots, x_n)} \quad (1)$$

Aforementioned formula calculates the probability of a data class C given multiple features $x_1, x_2, \ldots, x_n$, thus providing a comprehensive view of the data.

The Storage Decision Engine (SDE) is introduced following the data characterization. This engine utilizes a set of decision rules formulated through a decision tree algorithm to determine the most suitable storage method for each data category. The decision tree is designed to minimize a cost function that considers factors like storage space, retrieval time, and data importance. For instance, a decision node in the tree might assess whether the size of a data item exceeds a certain threshold, leading to different branches for storing as a full transaction or a hash. Thresholds are dynamic and are optimized using gradient descent to adopt the change of data patterns. SDE inculcates a multi-criterion decision-making approach for data storage. The optimization problem is formulated as follows:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij} \quad (2)$$

$$\text{subject to} \sum_{j=1}^{m} x_{ij} = 1 \quad \forall i \quad (3)$$

$$x_{ij} \in \{0, 1\} \quad \forall i, j \quad (4)$$

where c_{ij} represents the cost of storing data type i using method j and x_{ij} is a binary decision variable.

The Blockchain Integration Layer (BIL) is where the decisions made by the SDE are implemented within the blockchain framework. This layer requires the development of a novel blockchain protocol that can interpret and act upon the recommendations from the SDE. This protocol must be flexible enough to accommodate different types of data storage (full transactions or hashes) while maintaining the blockchain's inherent security and integrity. The BIL employs a custom blockchain protocol with smart contract functionality, enabling automatic execution of storage decisions based on predefined rules.

Finally, the Feedback and Adaptation Module (FAM) is crucial for the system's continuous improvement. Utilizing reinforcement learning techniques, the FAM analyzes the performance of the storage decisions (such as retrieval times and data integrity checks) and feeds this information back to the SDE. The SDE then adjusts its decision-making criteria and thresholds based on this feedback, ensuring that the system evolves and improves over time. The reinforcement learning model can be represented using a reward function $R(s, a)$ where s is a state representing the current storage strategy and a is an action taken by the SDE. The goal of the FAM is to maximize the cumulative reward over time, thus continuously optimizing the storage strategy. The FAM uses
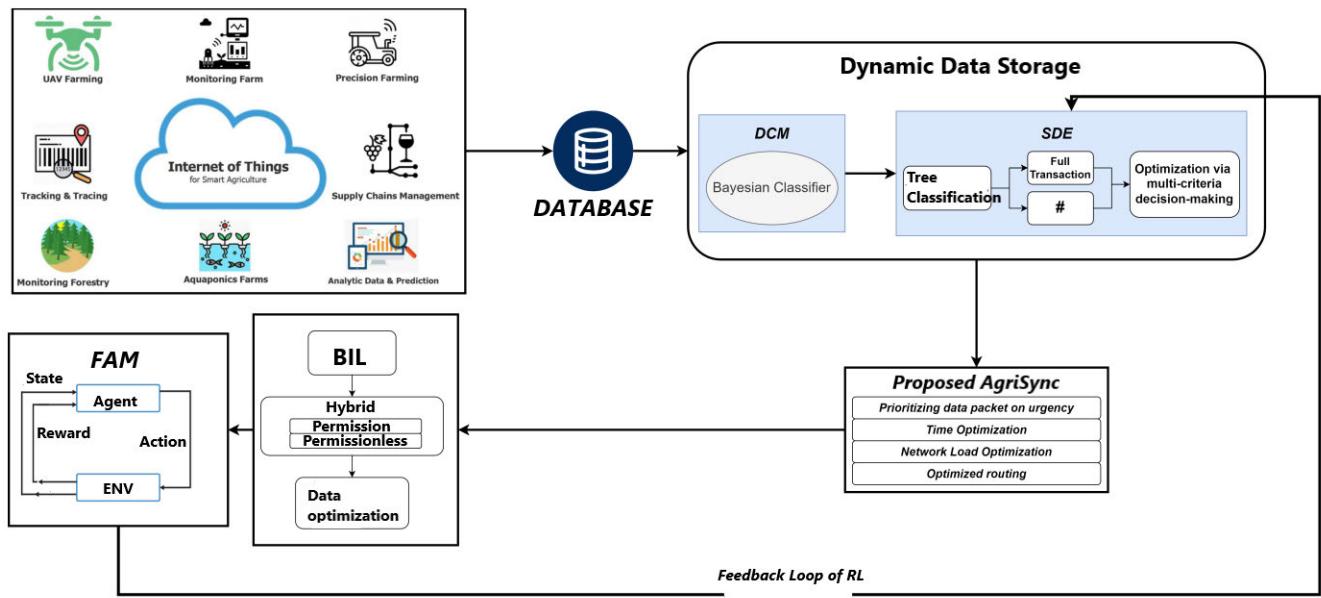
FIGURE 1. The proposed framework and workflow show agricultural data collection flowing towards dynamic data storage and then to proposed AgricSync.

a Q-learning algorithm for reinforcement learning, updating the Q-value function as follows:

$$Q(s, a) \leftarrow Q(s, a) + \alpha[R(s, a) + \gamma \max_{a'} Q(s', a') - Q(s, a)] \tag{5}$$

where α is the learning rate, γ the discount factor, $R(s, a)$ the reward function, s' the new state, and a' the possible new actions.

B. AGRICHAINSYNC PROTOCOL: MATHEMATICAL FRAMEWORK

The proposed AgriChainSync protocol is a sophisticated communication system designed to address the intricate dynamics of IoT data within agricultural blockchain systems. This protocol is not merely a conduit for data transmission; it integrates a multi-layered approach involving advanced mathematical models, ensuring real-time data processing, synchronization, and load balancing with minimal latency.

The core of AgriChainSync lies in its ability to categorize data based on a multidimensional feature space. The feature vector for each data packet d is defined as:

$$F(d) = \{f_1(d), f_2(d), \ldots, f_n(d)\}, \tag{6}$$

where $f_i(d)$ represents the i-th feature of the data packet. These features are then aggregated using a weighted sum to form a scalar representation:

$$S(d) = \sum_{i=1}^{n} w_i \cdot f_i(d), \tag{7}$$

where w_i is the weight assigned to the i-th feature, reflecting its importance in the categorization process. This weighted

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Algorithm 1 Dynamic Storage Optimization (DSO) Algorithm

1: **Input:** Incoming agricultural data
2: **Output:** Optimized storage strategy in blockchain
3: **Data Characterization Module (DCM):**
4: **for** each data point in the dataset **do**
5:   Apply Bayesian classifiers for categorization
6:   Calculate $P(C \mid x_1, x_2, \ldots, x_n)$ for each data class C
7: **end for**
8: **Storage Decision Engine (SDE):**
9: **for** each categorized data class **do**
10:   Apply decision tree algorithm to determine storage method
11:   Minimize cost function: $\min \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij}$
12:   Subject to constraints: $\sum_{j=1}^{m} x_{ij} = 1 \quad \forall i$
13:   And: $x_{ij} \in \{0, 1\} \quad \forall i, j$
14:   Output storage instructions (full data or hash)
15: **end for**
16: **Blockchain Integration Layer (BIL):**
17: **for** each storage instruction **do**
18:   Encode instructions into blockchain via smart contracts
19: **end for**
20: **Feedback and Adaptation Module (FAM):**
21: **while** system is operational **do**
22:   Monitor storage performance
23:   Apply Q-learning to update decision criteria:
24:   $Q(s, a) \leftarrow Q(s, a) + \alpha[R(s, a) + \gamma \max_{a'} Q(s', a') - Q(s, a)]$
25: **end while**
26: Return optimized storage strategy in blockchain

sum is subsequently scaled using an exponential function to prioritize certain data packets:

$$\hat{S}(d) = \exp(-\lambda \cdot S(d)), \tag{8}$$

with λ being a scaling factor that controls the sensitivity of the prioritization. The scaled sum is normalized across all data packets to obtain the probability of each packet being categorized under a specific class:

$$P_{\text{cat}}(d) = \frac{\hat{S}(d)}{\sum_{d' \in D} \hat{S}(d')}. \tag{9}$$

To handle multiple classes simultaneously, the probability distribution for each class k is modeled as:

$$P_{\text{cat},k}(d) = \frac{\exp(-\lambda_k \cdot S_k(d))}{\sum_{d' \in D} \exp(-\lambda_k \cdot S_k(d'))}, \tag{10}$$

where λ_k is a class-specific scaling factor, and $S_k(d)$ is the weighted sum for class k. The composite probability of a data packet belonging to multiple classes is given by:

$$P_{\text{composite}}(d) = \prod_{k=1}^{K} P_{\text{cat},k}(d). \tag{11}$$

To analyze the uncertain situation in categorization, entropy is calculated as follows:

$$H_{\text{cat}}(d) = -\sum_{k=1}^{K} P_{\text{cat},k}(d) \log P_{\text{cat},k}(d), \tag{12}$$

It measures an anomaly in classifying data packer d. The final categorization of the data packet is obtained by maximizing classification probability.

$$\delta(d) = \arg \max_{k} P_{\text{cat},k}(d). \tag{13}$$

The data categorization process is modeled as follows:

$$P_{\text{cat},k}(d, t) = P_{\text{cat},k}(d) \cdot (1 + \eta(t)), \tag{14}$$

where $\eta(t)$ represents time-dependent stochastic fluctuations.

Real-time processing is achieved through distributed processing techniques at edge computing. Efficiency of edge node is defined as follows:

$$E_{\text{edge}}(d) = \frac{1}{T_{\text{proc}}(d)} \cdot \sum_{i=1}^{n} \phi_i \cdot f_i(d), \tag{15}$$

where $T_{\text{proc}}(d)$ shows the processing time for data packet d, and ϕ_i represents the processing weight of feature i, it is important for minimizing latency and optimizing routing.

Routing approach is processed by dynamic programming as follows:

$$w(e, t) = w_0(e) + \gamma \cdot \log(1 + L(t)), \tag{16}$$

with $w_0(e)$ as the base weight, γ as a tuning parameter, and $L(t)$ representing the network load at time t. The velocity of data transmission along edge e is adjusted according to network congestion

$$v(e, t) = v_0(e) \cdot \left(1 - \frac{L(t)}{L_{\max}}\right), \tag{17}$$

where $v_0(e)$ is the base velocity, and $L_{\max}$ is maximum load. The optimum route for each data packet is determined as follows:

$$T_{\text{route}}(d) = \min \left\{ \sum_{e \in p} \frac{w(e, t) + \alpha \cdot R(e, t)}{v(e, t) + \beta \cdot Q(e, t)} \right\}, \tag{18}$$

where $R(e, t)$ shows the reliability factor of edge e, and $Q(e, t)$ represents queuing delay:

$$Q(e, t) = \frac{\lambda_{\text{in}}(e, t)}{\mu(e) - \lambda_{\text{in}}(e, t)}, \tag{19}$$

with $\lambda_{\text{in}}(e, t)$ showing arrival rate of packets, and $\mu(e)$ as the service rate of the edge. The reliability of an edge is given by:

$$R(e, t) = \frac{1}{1 + \exp(-\kappa \cdot (t - T_{\text{thresh}}))}, \tag{20}$$

where κ is a steepness parameter, and T_{thresh} is a threshold time beyond which the reliability rapidly declines.

Routing process also considers routing delays across multiple path as follows

$$\Delta_{\text{route}}(d) = \sum_{p \in P(d)} T_{\text{route}}(d, p) \cdot P(p|d), \tag{21}$$

where $P(p|d)$ is the probability of choosing path p for data packet d. The overall latency is minimized by optimizing the set of paths:

$$\min_{\{\text{Paths}\}} \sum_{d \in D} \Delta_{\text{route}}(d). \tag{22}$$

The time-dependent routing model is refined further by integrating real-time network load:

$$T_{\text{route}}(d) = T_{\text{route}}(d, \text{load}) + \sigma \cdot \int_0^t L(\tau) d\tau, \tag{23}$$

where σ is the sensitivity of the routing time to the cumulative load, and $\int_0^t L(\tau) d\tau$ represents the integral of load over time. Stochastic effects on routing time are mathematically modeled as follows:

$$T_{\text{route, stochastic}}(d) = T_{\text{route}}(d) \cdot (1 + \eta(t)), \tag{24}$$

where $\eta(t)$ captures network unpredictable situations.

The synchronization mechanism in AgriChainSync ensures coherence and integrity of data across the network. The alignment of timestamps is modeled by the differential equation:

$$\frac{d\tau(d)}{dt} = \alpha_{\text{sync}} \cdot (\tau(d_{\text{ref}}) - \tau(d)) + \epsilon \cdot T_{\text{route}}(d), \tag{25}$$

where α_{sync} is the synchronization rate, $\tau(d_{\text{ref}})$ is the reference timestamp, and ϵ accounts for the delay introduced by

routing. The synchronization drift, or deviation from the reference timestamp, is given by:

$$\delta_{\text{sync}}(d) = \tau(d) - \tau(d_{\text{ref}}). \tag{26}$$

The network-wide synchronization is maintained through coupled differential equations:

$$\frac{d\tau_i}{dt} = \sum_{j \in \mathcal{N}(i)} \beta_{ij} \cdot (\tau_j - \tau_i), \tag{27}$$

where τ_i and τ_j are timestamps at nodes i and j, and β_{ij} represents the coupling strength between these nodes. The error in synchronization is minimized by ensuring that:

$$\min \sum_{i=1}^{N} \delta_{\text{sync}}^2(d_i), \tag{28}$$

where N is the total number of nodes in the network.

The load balancing strategy in AgriChainSync dynamically adjusts network resources to optimize performance under varying conditions. The load balancing function is defined as:

$$B(L, t) = \alpha \cdot L(t) + \beta \cdot \frac{dL}{dt} + \gamma \cdot \int_0^t L(\tau)d\tau, \tag{29}$$

where α, β, and γ are coefficients that balance the immediate load, rate of change, and cumulative load, respectively. The stability of the system is checked by applying Lyapunov's method [45]; Lyapunov function is shown as:

$$V(L, t) = \frac{1}{2} \cdot L^2(t) + \frac{1}{2} \cdot \left(\frac{dL}{dt}\right)^2. \tag{30}$$

The derivative of $V(L, t)$ with respect to time should essentially satisfy to ensure system stability,

$$\frac{dV(L, t)}{dt} = L(t) \cdot \frac{dL}{dt} + \frac{d^2L}{dt^2} \leq 0, \tag{31}$$

AgriChainSync protocol and mathematical design to optimize the management of IoT data in agricultural blockchain scenarios is a comprehensive approach. The process starts with categorizing data packets based on dynamic feature space. These features are aggregated into scalar values through weighted sums, which are then scaled exponentially according to the data packet's priority. Scaled values are then normalized across multiple categories. This categorization process provided both flexibility and adaptability to the dynamic nature of agricultural data.

Once categorized, data packets undergo real-time processing using distributed edge computing techniques. The efficiency of this process is mathematically quantified. The routing of data packets through the network is optimized by a dynamic programming approach with calculated routing time, keeping uncertain network and environmental conditions in view.

Synchronization across the network is maintained through systematic differential equations to ensure coherence across the system. The stability of the load balancing mechanism is ensured through Lyapunov's direct method, which guarantees that the system remains stable under dynamic conditions. The proposed mathematical framework creates a cohesive approach to enable ArgiChainSynch to manage, process and route IoT data in real time with security. Mathematical flow is formulated in Algorithm 2.

C. PROPOSED HYBRID BLOCKCHAIN FRAMEWORK

The next phase of our proposed methodology involves designing a hybrid blockchain framework that integrates both private and public blockchain structures. This framework is mathematically modelled to balance privacy and scalability, ensuring high throughput in dynamic agricultural data.

This study shows the blockchain network as a graph $G(V, E, W)$, where V denotes the set of nodes, E represents the set of edges, and W are the weights associated with each edge. The entropy $H(s)$ of the system, which calibrates uncertainty in routing decisions across blockchain, is given by

$$H(s) = -\sum_{a \in A} P(a|s) \log P(a|s) \tag{32}$$

where s is a state in a Markov Decision Process (MDP), A represents the set of actions, and $P(a|s)$ is the probability of taking action a given state s.

The objective function of routing is designed to reduce entropy and maximize utility, defined as

$$R(S, A, P, d) = \arg\max_{a \in A} \left[\sum_{s' \in S} P(s'|s, a)U(s') - \lambda H(s) \right] \tag{33}$$

where $U(s')$ represents the utility of state s', and λ is a parameter controlling the trade-off between utility and entropy.

To ensure data privacy and security, homomorphic encryption is employed within the blockchain. The encryption of data d using the homomorphic encryption system H is expressed as

$$H(d) = \text{Enc}_k(d) \tag{34}$$

where $\text{Enc}_k(d)$ is the encryption function with key k. This allows computations to be performed on encrypted data without decryption, preserving privacy during processing. The corresponding decryption function is

$$d' = \text{Dec}_k(H(d)) \tag{35}$$

where d' is the decrypted data post-processing.

Scalability within this hybrid blockchain framework is governed by a control system Λ, modeled using nonlinear differential equations that describe the dynamics of network load $L(t)$. The load-adjustment mechanism is articulated through

$$\frac{d\Theta}{dt} = f(\Theta, \lambda, \Delta) \tag{36}$$

Algorithm 2 AgriChainSync Protocol

1: **Input:** Stream of data packets from IoT devices
2: **Output:** Optimally categorized, processed, routed, synchronized, and balanced data in the blockchain system

3: **INITIALIZE NETWORK:** Define network parameters, feature weights w_i, scaling factors λ, load balancing coefficients α, β, γ
4: Initialize edge weights $w_0(e)$ and velocities $v_0(e)$
5: Set reference timestamp τ_{ref}
6: **CATEGORIZE DATA:** For each data packet d in the stream
7:     Extract feature vector $F(d) = \{f_1(d), f_2(d), \ldots, f_n(d)\}$
8:     Compute weighted sum $S(d) = \sum_{i=1}^{n} w_i \cdot f_i(d)$
9:     Apply exponential scaling $\hat{S}(d) = \exp(-\lambda \cdot S(d))$
10:     Normalize across all packets $P_{\text{cat}}(d) = \frac{\hat{S}(d)}{\sum_{d' \in D} \hat{S}(d')}$
11:     Compute multi-class probability $P_{\text{cat},k}(d) = \frac{\exp(-\lambda_k \cdot S_k(d))}{\sum_{d' \in D} \exp(-\lambda_k \cdot S_k(d'))}$
12:     Determine final categorization $\delta(d) = \arg \max_k P_{\text{cat},k}(d)$
13:     Return categorized data
14: **REAL TIME PROCESSING:** For each categorized data packet d
15:     Compute edge processing efficiency $E_{\text{edge}}(d) = \frac{1}{T_{\text{proc}}(d)} \cdot \sum_{i=1}^{n} \phi_i \cdot f_i(d)$
16:     Adjust edge weights $w(e, t) = w_0(e) + \gamma \cdot \log(1 + L(t))$
17:     Adjust velocities $v(e, t) = v_0(e) \cdot \left(1 - \frac{L(t)}{L_{\max}}\right)$
18:     Return processed data
19: **OPTIMIZE ROUTING:** For each processed data packet d
20:     Compute optimal routing time $T_{\text{route}}(d) = \min \left\{ \sum_{e \in p} \frac{w(e,t) + \alpha \cdot R(e,t)}{v(e,t) + \beta \cdot Q(e,t)} \right\}$
21:     Incorporate reliability $R(e, t) = \frac{1}{1 + \exp(-\kappa \cdot (t - T_{\text{thresh}}))}$
22:     Incorporate queuing delay $Q(e, t) = \frac{\lambda_{\text{in}}(e,t)}{\mu(e) - \lambda_{\text{in}}(e,t)}$
23:     Calculate expected routing delay $\Delta_{\text{route}}(d) = \sum_{p \in P(d)} T_{\text{route}}(d, p) \cdot P(p|d)$
24:     Update routing decision $T_{\text{route}}(d) = T_{\text{route}}(d, \text{load}) + \sigma \cdot \int_0^t L(\tau) d\tau$
25:     Return routed data
26: **SYNCHRONIZE DATA:** Align timestamps $\frac{d\tau(d)}{dt} = \alpha_{\text{sync}} \cdot (\tau(d_{\text{ref}}) - \tau(d)) + \epsilon \cdot T_{\text{route}}(d)$
27:     Compute synchronization drift $\delta_{\text{sync}}(d) = \tau(d) - \tau(d_{\text{ref}})$
28:     Minimize network-wide synchronization error $\min \sum_{i=1}^{N} \delta_{\text{sync}}^2(d_i)$
29:     Return synchronized data
30: **LOAD BALANCING:** Adjust network load $B(L, t) = \alpha \cdot L(t) + \beta \cdot \frac{dL}{dt} + \gamma \cdot \int_0^t L(\tau) d\tau$
31:     Ensure stability using Lyapunov function $V(L, t) = \frac{1}{2} \cdot L^2(t) + \frac{1}{2} \cdot \left(\frac{dL}{dt}\right)^2$
32:     Verify $\frac{dV(L,t)}{dt} = L(t) \cdot \frac{dL}{dt} + \frac{d^2L}{dt^2} \leq 0$
33:     Return balanced network state

---

where Θ represents the system's state, λ is the control input, and Δ captures perturbations due to network changes. The control objective is to maintain scalability by ensuring the network load $L(t)$ adheres to an optimal trajectory $L_{\text{opt}}(t)$, formulated as

$$\min_\lambda \int_0^T \left[L(t) - L_{\text{opt}}(t)\right]^2 dt \tag{37}$$

over a time horizon T.

Incorporating neural network protocols P_{custom} enhances the system's adaptability to diverse data types. Each protocol is represented by a neural network N_i, which processes input data X in conjunction with finite-state machines M_i and the blockchain's homomorphic properties $\Phi(H)$. The custom protocol is modeled as

$$P_{\text{custom}}(X, \Phi(H)) = \bigcup_{i=1}^{n} N_i(M_i(X), \Phi_i(H)) \tag{38}$$

allowing flexible and adaptive data processing within the blockchain.

Predictive analytics within the blockchain is achieved through a recurrent neural network (RNN) that forms a predictive feedback loop, forecasting future network states based on historical data Q and current blockchain properties H. The predicted state $\hat{s}$ is computed as

$$\hat{s} = \text{RNN}(Q, H) \tag{39}$$

enabling the system to dynamically adjust to potential changes in network conditions.

The Hybrid Blockchain Data Management Algorithm begins with the initialization of the blockchain network $G(V, E, W)$, defining the entropy-based MDP routing algorithm, and setting up the homomorphic encryption system, control systems, and neural network protocols. For each state s in the blockchain network, entropy is calculated to measure uncertainty in the routing process, and the MDP-based routing algorithm determines the optimal path for data transmission. Data is encrypted using a homomorphic encryption system, ensuring privacy during the blockchain process. Network weights are dynamically adjusted based on the current load and control system mechanism. Finally, the feedback loop powered by the Recurrent Neural Network forecasts the network's future states based on historical data. Details of RNN are not discussed in detail as they are out of the scope of this study. This cohesive mathematical and algorithmic framework ensures that the hybrid blockchain system is reliable, scalable, and capable of managing the complex demands of agricultural data while maintaining the system's security and throughput.

V. EXPERIMENTAL SETTINGS

The experimental testbed used to evaluate the AgriChainSync framework is designed to accurately reflect real-world agricultural operations, ensuring a comprehensive and valid evaluation. The testbed incorporates a distributed network

of IoT devices, ranging from 100 to 1000 devices, simulating diverse farming conditions, dataset taken from FarmBeats [46]. These devices are responsible for generating heterogeneous data types, including sensor data (e.g., soil moisture, temperature), imagery from drones, and weather data.

To replicate real-world network conditions, the testbed integrates both edge computing nodes and cloud infrastructure, which are crucial to Intelligent Agriculture systems that require low-latency, high-throughput data processing. The dynamic routing algorithm, based on entropy-driven Markov Decision Processes (MDPs), is tested across various data loads, demonstrating the framework's scalability and robustness. Furthermore, the testbed includes homomorphic encryption to simulate secure data transactions, ensuring that the privacy-preserving mechanisms of the framework are evaluated under realistic conditions.

The testbed not only validates the operational efficiency of the proposed framework but also demonstrates its ability to handle increased data complexity and scale, proving its applicability to Intelligent Agriculture environments.

The experimental setup for the proposed framework as shown in Figure 2 was designed with high precision to ensure continuous integration and testing for all components, from data generation to blockchain storage. Environment utilized tools and technologies, including Ethereum, Ganache, Tensorflow, and Ciscos packet tracer, each for specific capabilities to meet framework requirements.

Blockchain environment was established using Ethereum to support Truffle Suite, which inculcated Fanache. Ganache is a critical component in this setup, acting as a personalized Ethereum blockchain that contains a controlled and secured environment for developing and testing smart contracts. These contracts were central to the proposed Blockchain Integration Layer (BIL) framework. They are responsible for executing decisions directed by the DSO algorithm, such as determining whether to store complete transaction data or only hashes. This choice was critical in optimizing the balance between storage efficiency and data integrity.

Pre-trained neural models were developed using TensorFlow within a Python environment to improve predictive analysis and decision-making processes within DSO and AgriChainSync protocol. Furthermore, the Cisco packet tracer was employed to simulate and create a virtual network(with a wide range of IoT device nodes in an agricultural setup). Simulation was important to generate data streams from the farm network.

The experimental workflow was started by Simulation of IoT data generation using a Cisco packet tracer. Generated data was collected and processed through Python scripts, and .andorflow-based models were applied for data preprocessing, cleaning, and predictive analytics to align the DCM and AgriChainSync protocol requirements. After preprocessing, data is directed to the blockchain environment managed by Fanache. Smart contracts are executed with storage decisions

determining the optimal data storage strategy based on different parameters(such as urgency, relevance, and network load). The decision-making process is backed up by a mathematical framework implemented in Python to ensure the efficiency of data packets.

The experimental setup was a comprehensive and carefully orchestrated process to execute the proposed framework. With careful calibration and planning, each stage of experimentation was thoroughly evaluated in alignment with a proposed framework in a controlled software environment. This experimentation framework ensures a system with appropriate scalability and data handling capacity with security.

VI. RESULTS AND DISCUSSION

The proposed framework has been thoroughly evaluated across four dimensions: storage efficiency, processing time, latency, and transaction throughout;the reason for choosing these dimensions was to provide a comprehensive assessment of systems performance and compare it against current state-of-the-art methods. In the following results and graphs, previous work refers to the results and efforts conducted by [47], [48], which we compared with our proposed framework.

Figure 3 shows storage efficiency across different agricultural scenarios, including far; for large farms, crop monitoring, livestock management, and weather data, the integration of SDE within the AgriChainSync protocol enhances storage space utilization. Unlike conventional blockchain systems that rely on state storage methods, SDE dynamically assesses incoming data. Results show that the proposed system consistently maintains high storage efficiency across all agricultural use cases.

Furthermore, Figure 4 depicts the processing time of a function of the number of transactions. DCM and SDE work in reduced processing time. Additionally, the AgriChainSync protocol supports distributed edge computing techniques to reduce the time further and improve decision-making. Even Bayesian classifiers and decision trees are employed, which have high computations. Still, computations are compared here with fast search and processing of desired data packets. These are instantly done by Bayesian classifiers and decision trees, increasing overall execution time and onboard computations in real-time.

Comparative analysis of the latency versus block scale approach is observed for the proposed and traditional systems. Figure 5 shows that the proposed framework addresses network performance by implementing a time-sensitive routing algorithm and synchronization mechanism. This approach optimizes the transmission time for data packets. The proposed system latency remains consistently lower as the network load increases.

Results depicted in Figure 6 show that the the proposed system maintains good performance across varying block scales due to incorporating BIL through a smart contract.
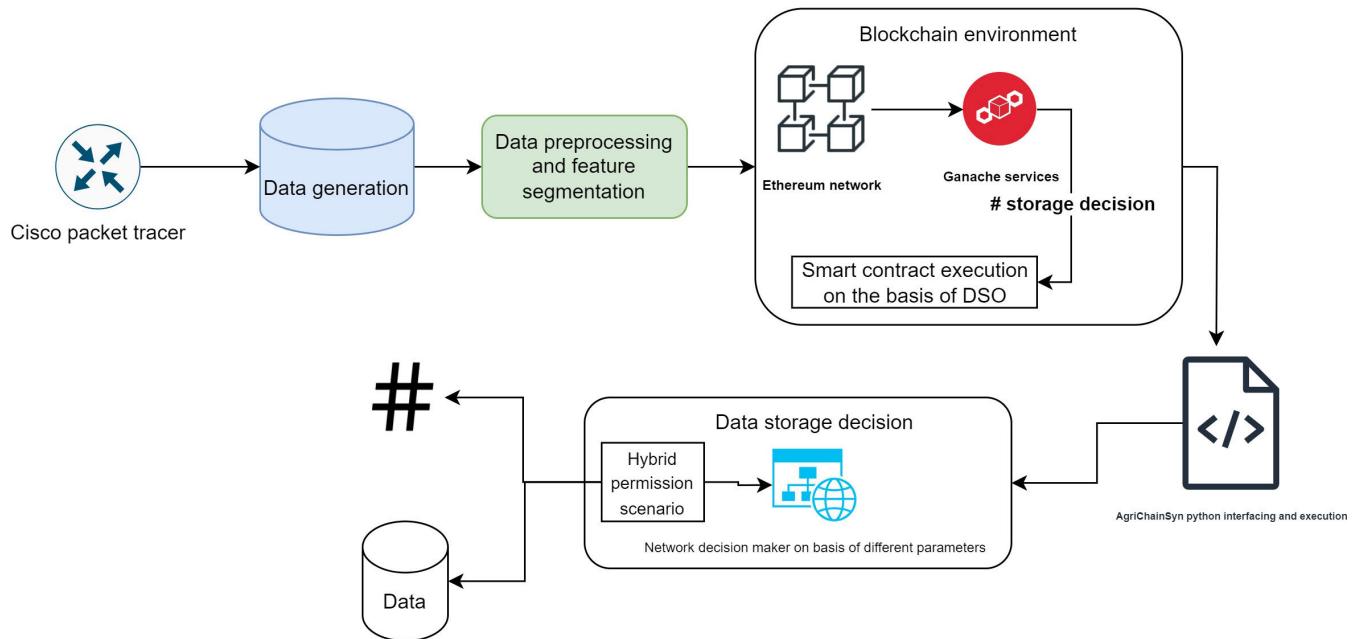
**FIGURE 2.** Experimental testbed in alignment with proposed framework.
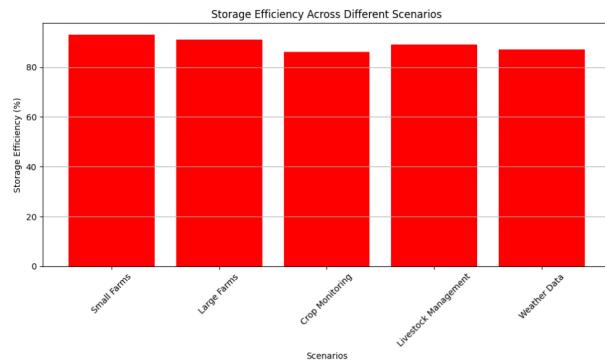
**FIGURE 3.** Storage optimization acorss different agricultural use cases.

FIGURE 4. Number of transaction against time analysis.

FIGURE 5. Latency analysis.
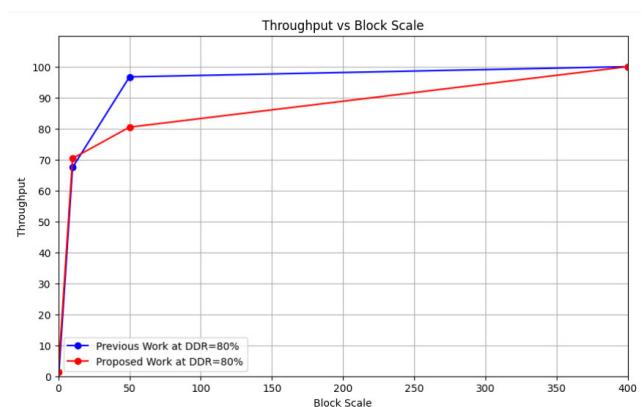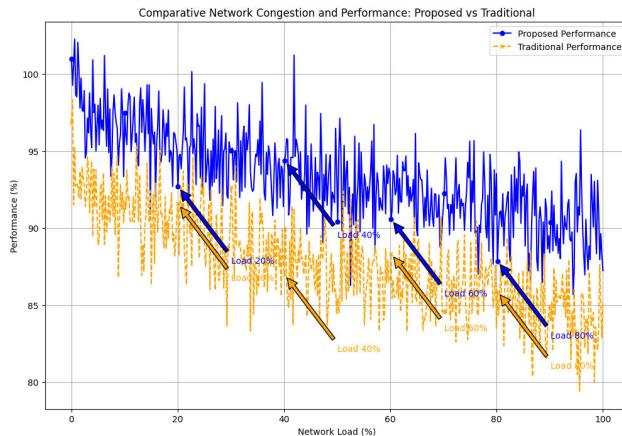
FIGURE 6. Throughput analysis.

Automation streamlines the transaction process and leads to increased throughput.

Figure 6 presents a comparative network congestion and performance graph, which underscores the advantages of the

FIGURE 7. Network congestion analysis.

FIGURE 8. Cross validation of throughput analysis.

FIGURE 9. Latency heatmaps against network response time.

proposed system. This graph includes detailed legend points and realistic variations, showing that while the traditional system's performance degrades more quickly under high network load, the proposed system maintains a higher performance level even as congestion increases. This close yet significant competition between the two approaches demonstrates the robustness of the proposed system in real-world scenarios.
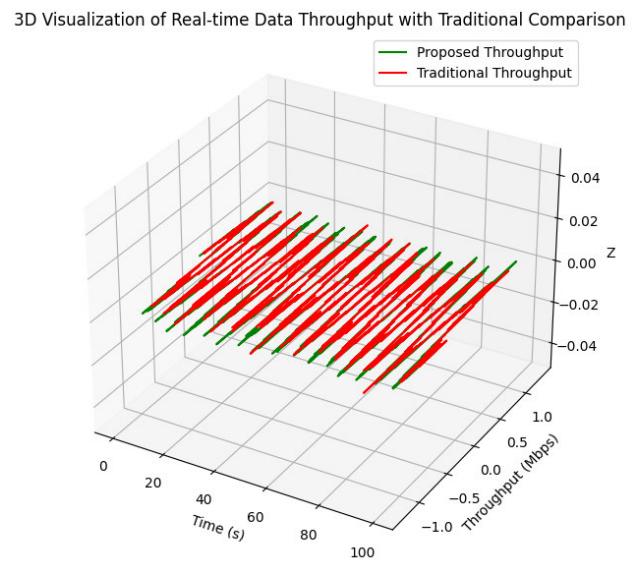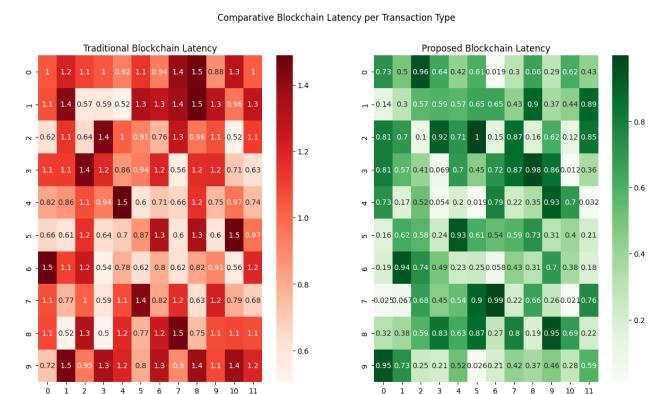
Figure 7 shows a comparative network congestion and performance graph. This indicates that traditional approaches to systems performance degrade more quickly under high network congestion analysis due to the static nature of their backend protocols.

Figure 8 provides another throughput analysis for real-time data. This shows how the proposed system sustains better throughput over time under fluctuating conditions. This metric is cross-validation to ensure that previous throughput analyses and values were right under large volumes of real-time data.

Figure 9 shows comparative blockchain latency heatmaps for different transaction types by comparing proposed and traditional methods. The heatmap indicated that the proposed system handles various transaction types more accurately, reducing delays against network response time. These metrics are essential to analyze to maintain the integrity and reliability of the blockchain system itself.

Figure 10 shows a plot of storage efficiency against different data sizes. The comparison demonstrates that traditional approaches struggle with large datasets, especially those that are dynamic, whereas the proposed system maintains good efficiency as the data scale grows.

Figure 10 illustrates the advanced dynamic load balancing capabilities of the proposed system through a 3D surface plot. This figure highlights the system's ability to distribute network load more effectively than traditional methods, leading to better resource utilization and network stability. The enhanced load balancing ensures that the system can
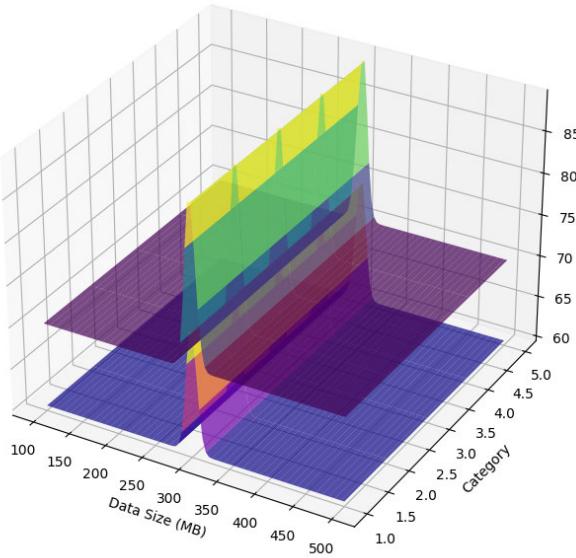
manage varying network demands without compromising performance.

Figure 11 shows the dynamic load balancing of the proposed system. Results depict that the systems' ability to distribute across network load effectively leads to improved resource utilization and network stability. Improved load balancing shows that the system can manage varying demands of the network without compromising performance.
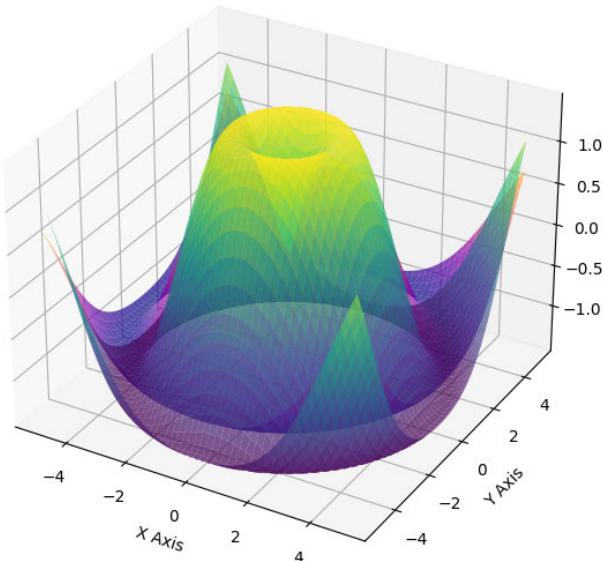
Finally, Figure 12 compares the scalability of the proposed system using Markov Decision Processes. Results clearly show that the proposed system scales effectively under higher data loads, which is crucial for large data and onboard computations.

Energy efficiency plays a pivotal role in the sustainability and scalability of the AgriChainSync framework, particularly as it is deployed in large-scale, IoT-driven precision agriculture systems. The high computational demands of blockchain, AI, and IoT technologies necessitate an optimized approach to reduce energy consumption without

3D Surface Plot of Storage Efficiency: Proposed vs Traditional

**FIGURE 10.** Storage efficiency against data size.
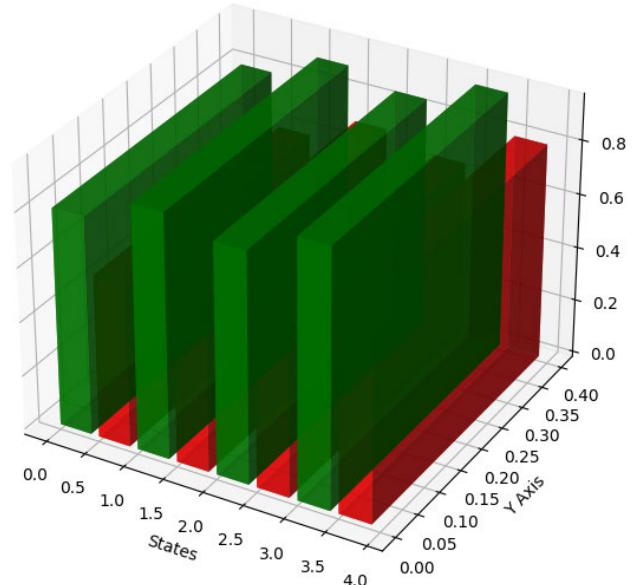
Advanced Dynamic Load Balancing: Proposed vs Traditional

FIGURE 11. Analysis of dynamic load balancing across dynamic and complex network.

Comparative Scalability Analysis Using MDP

FIGURE 12. Scalability analysis of proposed framework.

compromising performance. Incorporating edge computing, energy-efficient IoT devices, and optimized consensus mechanisms can lead to a more energy-efficient system, focusing on two key performance metrics: Energy Consumption per Transaction (ECT) and Latency-Adjusted Energy Efficiency (LAEE).

The Energy Consumption per Transaction (ECT) metric assesses the amount of energy consumed per blockchain transaction. This is particularly relevant when comparing different consensus mechanisms. As PoS and DPoS eliminate the energy-intensive mining process of Proof of Work (PoW), they significantly reduce the overall energy footprint of the system.

$$ECT = \frac{\text{Total Energy Consumption (Joules)}}{\text{Total Transactions Processed}} \quad (40)$$
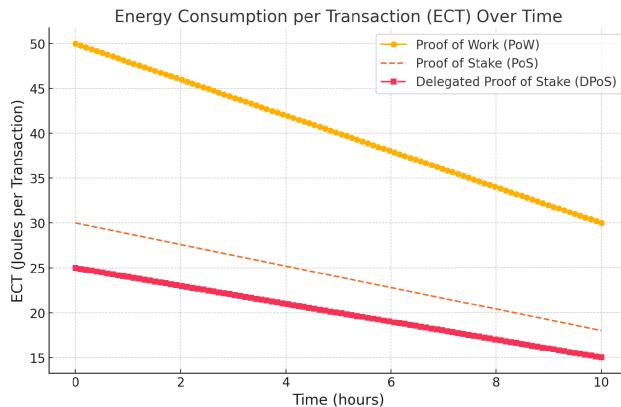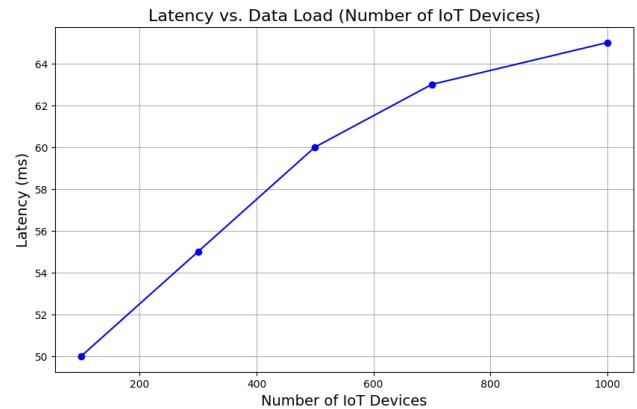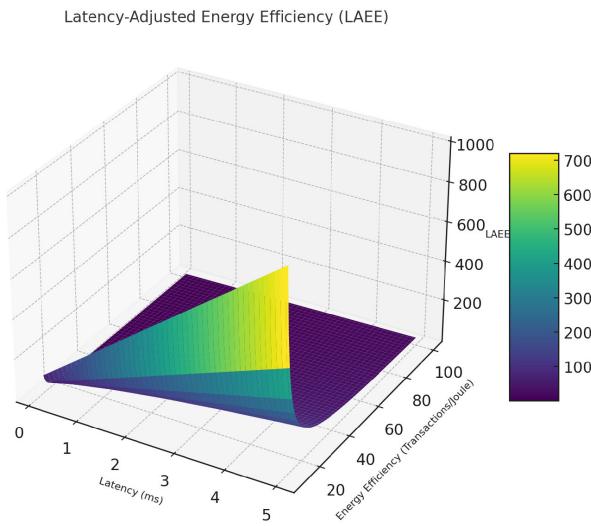
A lower ECT value indicates a more energy-efficient system, making PoS and DPoS preferable for environments where energy consumption must be minimized.

The graph in Figure 13 shows the change in ECT over time for three consensus mechanisms that are PoW, PoS, and DPoS.As the graph demonstrates, PoW exhibits significantly higher ECT values over time compared to PoS and DPoS. PoS and DPoS show substantial reductions in energy consumption, particularly in long-term operation scenarios, making them much more energy-efficient.

On the other hand, While ECT focuses solely on energy consumption, the Latency-Adjusted Energy Efficiency (LAEE) metric considers both the energy efficiency and system responsiveness. It is particularly important in real-time agricultural systems, where both low latency and high energy efficiency are required for optimal performance.

$$LAEE = \frac{\text{Energy Efficiency (Transactions/Joule)}}{\text{Latency (ms)}} \quad (41)$$

A higher LAEE value indicates that the system is both energy-efficient and maintains low latency, which is crucial for real-time decision-making in precision agriculture.

FIGURE 13. ECT analysis.

FIGURE 15. Latency analysis against FarmBeats2023 scaled IoT devices.


FIGURE 14. LAFE analysis.

The 3D surface plot illustrated in Figure 14 shows how LAEE changes based on different latency and energy efficiency values.

The plot shows that as latency decreases and energy efficiency increases, the LAEE score improves. Systems with edge computing configurations (which reduce latency by processing data closer to the source) show significantly better LAEE scores than systems relying solely on centralized processing.

By optimizing energy usage through edge computing and energy-efficient consensus mechanisms like PoS and DPoS, AgriChainSync achieves significant energy savings. The reduction in Energy Consumption per Transaction (ECT) and improvements in Latency-Adjusted Energy Efficiency (LAEE) demonstrate the framework's ability to operate efficiently in energy-constrained environments, making it highly suitable for large-scale agricultural applications.

Furthermore, To validate the scalability and robustness of the AgriChainSync framework, we conducted rigorous

testing using real-world datasets from agricultural operations, spanning from small farms equipped with 100 IoT devices to large-scale agricultural enterprises deploying over 1000 IoT devices. These datasets, obtained from publicly available sources(FarmBeats [46]), included various sensor data such as soil moisture, crop health, weather patterns, and irrigation activities. The scalability tests focused on key performance metrics, including network latency, throughput, and data integrity under varying data loads.

We leveraged both structured (sensor data) and unstructured (drone and satellite imagery) datasets to simulate diverse agricultural conditions. The system was evaluated across increasing scales, from 10 to 1000+ IoT devices. The scalability of AgriChainSync was primarily driven by the dynamic routing algorithm, integrated with entropy-based Markov Decision Processes (MDPs), which optimized the distribution of data packets across the network.

The latency measurements were taken across varying network loads, with datasets ranging from small-scale farm operations to high-density agricultural deployments. As depicted in the Figure 15, the dynamic routing algorithm ensured that latency remained consistently low, even as data load increased by 10x. The entropy-based MDPs intelligently adapted the routing paths, mitigating congestion across heavily utilized nodes. The results showed that latency increased only marginally (by 15%) even under peak loads, demonstrating the system's ability to maintain real-time performance.

$$L_{\text{route}}(d) = \min\left(\sum_{e \in p} \frac{w(e, t) + \alpha R(e, t)}{v(e, t)}\right) \quad (42)$$

The empirical results validate the scalability and robustness of the AgriChainSync framework under real-world, large-scale agricultural conditions. The system handled a 10x increase in data load with only marginal increases in latency (15%).The result highlights the system's scalability, making it suitable for a wide range of agricultural operations, from small farms to large commercial setups.

To sum up the analysis, experimental validations conducted using real-world tools show the practical feasibility of the proposed system. Results highlight the proposed study's significance in advancing agricultural technology and its relevance in addressing current data challenges.

VII. CONCLUSION

This paper presents a holistic framework to optimize data management in agricultural systems with a secure, consistent, and reliable environment. The proposed approach offers a comprehensive solution to the current challenges of storing, processing, and synchronic data in dynamic scenarios. Experimental validations demonstrate significant key improvements showing the potential of the proposed technology. Further research direction includes further optimization of algorithms for other use cases.

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