Research article

Agri-farming with computer vision, IoT and blockchain towards climate smart cultivation☆

Sajid Safeer [a] ⬡, Pierluigi Gallo [b] ⬡,*, Cataldo Pulvento [c] ⬡

[a] *School of Advanced Studies, University of Camerino, 62032, Italy*
[b] *Department of Engineering, University of Palermo, 90128, Italy*
[c] *Department of Soil, Food and Plant Sciences, University of Bari, 70126, Italy*

A B S T R A C T

Modern agriculture faces critical challenges such as climate change, food security and supply chain inefficiencies, which demand innovative solutions. Traditional farming systems often lack real time monitoring, data security and transparency, leading to wastefulness and quality concerns. To address these, we present a comprehensive precision agriculture framework that integrates Internet of Things (IoT) sensors, Raspberry Pi (R-Pi) edge computing, blockchain based data management and computer vision (CV) assisted statistical modeling. The system collects environmental data via a sensor network, processes it at the edge using R-Pi, and records summarized outputs on a secure Ethereum based blockchain using smart contracts. Simultaneously, CV modules perform real time quality assessment and anomaly detection. A Markov chain based stochastic model is employed to track quality degradation in high value crops. The methodology is validated through a saffron use case, demonstrating effectiveness in monitoring filament degradation and detecting potential fraud. This integration enhances real time decision making, ensures traceability and promotes sustainability in climate smart agriculture.

1. Introduction

Agriculture has undergone profound transformations over millennia, from its origins in Neolithic subsistence farming to successive revolutions that introduced mechanization, chemical fertilizers, and genetically modified crops. These historical shifts from the Neolithic and Arab Agricultural Revolutions to the Green Revolution have continuously redefined productivity, land use, and socio-economic dynamics [1–4]. Today, the sector faces increasingly complex challenges. Climate change, population growth, land degradation and the demand for resource efficiency place unprecedented pressure on agricultural systems [5–7]. Conventional farming methods, often characterized by limited monitoring and centralized data handling, are insufficient to meet these 21st-century demands. In response, the emergence of digital technologies is redefining what it means to farm intelligently. Climate Smart Agriculture (CSA) integrates sustainability and productivity by leveraging technologies such as greenhouse automation, precision irrigation, and sensor based monitoring. Among these, the Internet of Things (IoT) enables real time environmental sensing, while computer vision (CV) provides automated crop assessment and quality monitoring [8–10]. Together, these systems enhance responsiveness, reduce waste and facilitate data driven decisions. However, the increasing volume and sensitivity of agri-data demand secure and trustworthy mechanisms for storage and exchange. Blockchain technology, with its decentralized and

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tamper resistant architecture, addresses this concern by enabling immutable data logging, transparent audit trails and smart contract enforcement [11–13]. When integrated with IoT and CV, blockchain forms a robust backbone for traceability, authentication and fraud prevention across the agri-food supply chain. Despite their potential, these technologies are often deployed in isolation. There remains a critical gap in unified architectures that integrate CV, IoT and blockchain into a coherent, interoperable system tailored to the real-world constraints of precision farming.

Our research addresses this gap by proposing a modular architecture that combines IoT-based sensing, CV-driven analytics, and blockchain-enabled traceability into a scalable solution for high-value crops. To demonstrate practical feasibility, we apply the model to saffron production, leveraging stochastic modeling via Markov chains to track degradation and detect quality anomalies. Our framework provides a secure data pipeline, a smart contract-based validation layer and an experimental setup integrating real-time sensing and decentralized analytics.

The key contributions of this study are:

- **Comprehensive literature review**: Identification of limitations in existing approaches and the need for a unified framework.
- **Integrated CV-IoT-Blockchain architecture**: A modular design that combines real time monitoring, vision-based analytics, and blockchain security.
- **Data integrity and traceability**: A secure data management pipeline with tamper-resistant logging and automated validation through smart contracts.
- **Practical validation**: Application of the framework to saffron farming, demonstrating its effectiveness in quality monitoring and fraud prevention.

The remainder of this article presents the related work, details the design and implementation of the proposed system and discusses its validation through simulation and real world deployment, contributing to the development of resilient, transparent and sustainable agricultural ecosystems.

2. A unified literature analysis

Building upon the promising potential and technological synergies highlighted above, it becomes imperative to examine how the academic community has approached this integration. A systematic assessment of existing literature is essential to gauge current research trends, identify gaps, and validate the application of these advanced technologies in precision agriculture. Given the emerging nature of integrating CV-IoT-Blockchain for CSA, there are limited peer-reviewed studies available. To address this and to assess use cases, all relevant literature on integrated CV-IoT-Blockchain frameworks in precision agriculture was evaluated. Hence, in the first phase, a computable bibliometric exploration was conducted. This involved three key steps: selecting databases, including or excluding articles, and evaluating their relevance. We began by screening published articles written in English from the Scopus database, employing specific search terms and filters to gather the data.

```
1  TITLE-ABS-KEY ("Blockchain"* OR {Agri-food Traceability OR Oracle OR Supply Chain OR
      API OR Tracking OR Solidity OR Hash OR Data Mining OR Smart Contract OR Proof of
      Work OR Automatic Blockchain} AND "Agriculture"* OR {Precision Farming OR Agri-
      farm OR Greenhouse OR Climate Smart Agriculture OR Glasshouse OR Cultivation OR
      Hothouse OR Cropping OR Productivity OR Environment OR Atmosphere} AND "IoT"* OR {
      Sensors OR Raspberry pi OR Devices OR Node OR Instruments OR Microcontroller OR Wi
      -Fi OR Bluetooth OR Wireless Adaptor OR Machine Learning OR Artificial
      Intelligence}) AND LANGUAGE (english) AND PUBYEAR > 2016 AND PUBYEAR < 2024 AND
      DOCTYPE (ar or re)
```

2.1. Bibliometric analysis and document screening

After applying relevant filters, we identified an initial pool of 150 documents. These documents underwent data analysis and duplication checks, conducted in R (version 2023.09.0+463). Through this process, we refined our selection to 30 significant documents that aligned closely with our research objectives. Interestingly, none of these selected documents were published before 2020, underscoring a recent surge in interest and research at the intersection of CV-IoT-Blockchain and precision agriculture. The detailed screening and selection process is illustrated in Fig. 1, which outlines the stages of document recognition, screening and inclusion, highlighting the criteria used to refine the initial pool down to the most relevant studies.

2.2. Comparative analysis of research trends

Through an analysis of selected 30 articles, we examined key characteristics such as author, publication year, article type, core theme, integrated technologies and the type of agriculture addressed. These findings highlight the growing interest in leveraging advanced technologies such as CV, IoT and Blockchain to address critical challenges and drive transformative changes in agricultural practices. Table 1 provides a comprehensive summary of the contributions of each article to the domain of CV-IoT-Blockchain integrated CSA, with a particular focus on precision agriculture and related themes.
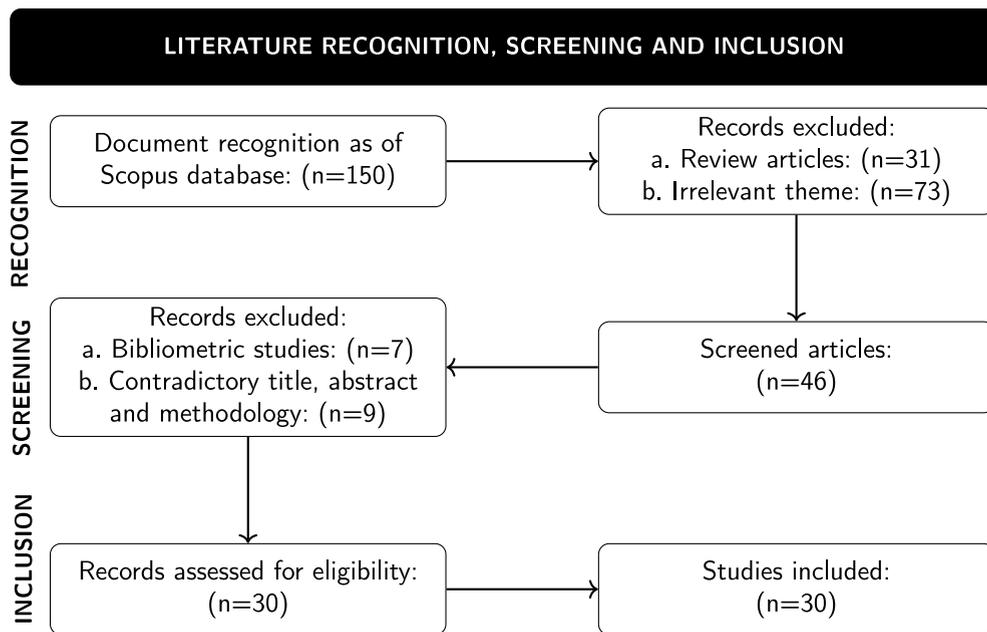
LITERATURE RECOGNITION, SCREENING AND INCLUSION

RECOGNITION

Document recognition as of Scopus database: (n=150)

Records excluded:
a. Review articles: (n=31)
b. Irrelevant theme: (n=73)

SCREENING

Records excluded:
a. Bibliometric studies: (n=7)
b. Contradictory title, abstract and methodology: (n=9)

Screened articles: (n=46)

INCLUSION

Records assessed for eligibility: (n=30)

Studies included: (n=30)

Fig. 1. Scopus screening and selection of significant documents.

- **Core Themes**: The predominant themes across the selected articles include data security, smart contracts, energy efficiency, crop yield optimization, and irrigation using advanced computer vision techniques. These themes highlight the focus on technological solutions that enhance security, efficiency, and productivity in agriculture.
- **Integrated Technologies**: A consistent trend observed in all studies is the integration of IoT with blockchain. This combination enhances data collection, automation, and traceability, enabling real-time monitoring and improved management in precision agriculture.
- **Agriculture Type**: The majority of the studies concentrate on precision agriculture, smart farming, digitalized agriculture, and greenhouse environments. This emphasis reflects the adaptability of CV, IoT, and blockchain technologies to diverse agricultural needs, particularly in ensuring data integrity, transparency, and sustainability.

3. Methodology and framework design

Following the Design Science Research (DSR) framework [44] well suited for tackling real-world challenges through artifact creation and systematic inquiry, our research progressed through four key phases: literature exploration and problem elaboration, requirements definition, design and development, demonstration and evaluation. We began with a comprehensive review of existing literature and real-world applications in smart farming and CSA. This analysis provided critical insights into technological gaps, enabling us to define essential system requirements such as real-time monitoring, data security, operational efficiency, and sustainable resource management. These requirements served as the foundation for designing and developing a novel architecture that integrates a diverse set of IoT devices and processing elements with blockchain technology. A distinctive aspect of our model is the incorporation of computer vision-assisted statistical modeling, which enhances data-driven decision making and optimizes agricultural processes. The prototype was developed through an iterative approach, structured into three main phases:
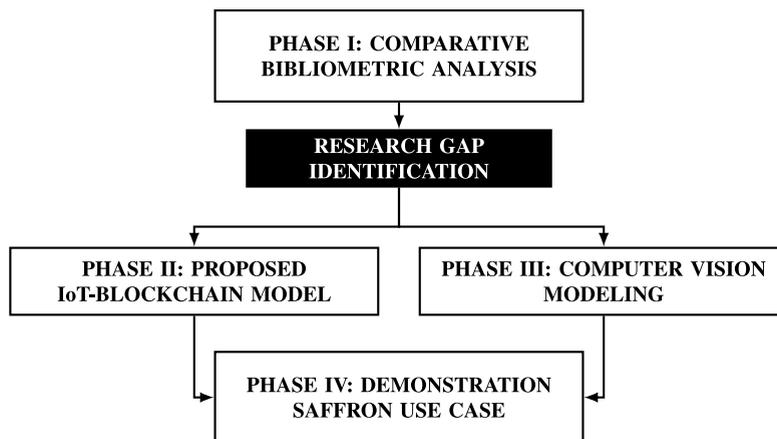
- **Core Development**: Implementation of fundamental components such as sensor networks for data acquisition and the blockchain infrastructure for secure data management.
- **Module Integration**: Embedding CV-assisted statistical modeling into the IoT-Blockchain framework to enable advanced analytics and real-time decision support.
- **System Refinement**: Optimizing overall system performance, including user interface enhancements and workflow efficiencies.

Each phase underwent rigorous iterative testing with specific validation criteria. For example, the core development phase required successful data capture and secure blockchain transactions, while the integration phase demanded robust performance of the CV analytics module. The final evaluation, demonstrated through a saffron farming use case, confirmed the model's potential to enhance the efficiency and resilience of smart agricultural systems. Fig. 2 illustrates the comprehensive research process followed in this study, showcasing how our integrated approach supports sustainable, automated, and secure CSA practices.

Table 1
A comparative analysis of relevant research efforts.

Author	Article	Year	Core Theme	CV	IoT	Blockchain	Agriculture
Torky and Hassanein [14]	Survey	2020	Integration	No	Yes	Yes	Precision
Iqbal and Butt [15]	Research	2020	Safety	No	Yes	Yes	Smart
Awan et al. [16]	Research	2020	Data Security	No	Yes	Yes	Precision
Ferrag et al. [17]	Survey	2020	Challenges	Yes	Yes	Yes	Green
Hossain et al. [18]	Research	2021	Data Security	No	Yes	Yes	Digitalized
Friha et al. [19]	Research	2021	Challenges	No	Yes	Yes	Smart
Guo et al. [20]	Research	2021	Integration	No	Yes	Yes	Smart
Chang et al. [21]	Research	2021	Irrigation	Yes	Yes	Yes	Smart
Awan et al. [22]	Research	2021	Energy	No	Yes	Yes	Precision
Pranto et al. [23]	Research	2021	Smart Contract	No	Yes	Yes	Smart
Pincheira et al. [24]	Research	2021	Irrigation	Yes	Yes	Yes	Smart
Anand and Sharma [25]	Research	2022	Data Security	No	Yes	Yes	Digitalized
Mangla et al. [26]	Research	2022	Integration	No	Yes	Yes	Precision
Ahmed et al. [27]	Research	2022	Integration	Yes	Yes	Yes	Smart
Sumathi et al. [28]	Research	2022	Crop Yield	Yes	Yes	Yes	Smart
Bodkhe et al. [29]	Survey	2022	Irrigation	No	Yes	Yes	Precision
Chaganti et al. [30]	Research	2022	Data Security	No	Yes	Yes	Digitalized
Abijaude et al. [31]	Research	2022	Data Security	No	Yes	Yes	Smart
Bera et al. [32]	Research	2022	Data Security	No	Yes	Yes	Digitalized
Anitha and Rai [33]	Research	2022	Crop Availability	Yes	Yes	Yes	Smart
Ghorbel et al. [34]	Research	2022	Crop Processing	Yes	Yes	Yes	Precision
Adow et al. [35]	Research	2022	Seed to Deal	Yes	Yes	Yes	Smart
Ting et al. [36]	Research	2022	Seed to Deal	Yes	Yes	Yes	Smart
Jamil et al. [37]	Research	2022	Smart Contract	Yes	Yes	Yes	Green House
Shreya et al. [38]	Research	2023	Seed to Deal	Yes	Yes	Yes	Cost Effective
Rehman et al. [39]	Research	2023	Seed to Deal	No	Yes	Yes	Smart
Patel et al. [40]	Research	2023	Seed to Deal	No	Yes	Yes	Smart
Frikha et al. [41]	Research	2023	Integration	Yes	Yes	Yes	Green House
Zeng et al. [42]	Research	2023	Irrigation	No	Yes	Yes	Precision
Hossain et al. [43]	Research	2023	Integration	Yes	Yes	Yes	Smart

Fig. 2. Hierarchical workflow of the Study.

4. System architecture

Building on insights gained from the comparative analysis of existing research, this section introduces a laboratory based novel IoT-Blockchain model tailored for intelligent agri-farms. Addressing the gaps identified in current agricultural infrastructure, the proposed framework integrates CV-IoT-Blockchain technologies to overcome challenges in precision cultivation. By aligning the model with stakeholder requirements and future technological trends, it demonstrates how CSA can benefit from enhanced efficiency, sustainability and transparency. This model serves as a practical implementation of the concepts explored in the previous sections, offering a foundation for the methodologies and case studies discussed in the subsequent sections.

At the core of the proposed framework lies a network of heterogeneous sensors tasked with collecting raw environmental data. These sensors, including DHT22 (temperature and humidity), YL-69 (soil moisture), BH1750 (light intensity) and analog pH sensors, are strategically deployed to monitor key environmental parameters. Each sensor connects via analog or interfaces to Raspberry Pi

Algorithm 1 Pseudo-code for CV-IoT-Blockchain Integration Framework
1: **Initialize IoT Sensors and Blockchain Network:**
2: - Connect IoT sensors (temperature, soil moisture, humidity, light, pH) to Raspberry Pi (R-Pi).
3: - Set up blockchain network with smart contract for data recording.
4: **Define Input Variables:**
5: - Sensor data: temperature, soil_moisture, humidity, light_intensity, pH.
6: - Blockchain parameters: contract_address, abi, private_key.
7: **Data Collection and Processing:**
8: - Fetch sensor data from IoT devices.
9: - Process raw data at R-Pi level to generate approximated actionable data.
10: **Blockchain Integration:**
11: - Use Python script to:
12: a. Retrieve processed data from R-Pi.
13: b. Construct and sign transactions.
14: c. Transmit data to blockchain via smart contract (updateWeather function).
15: **Stochastic Modeling for Quality Control:**
16: - Apply Markov chain model to track product degradation.
17: - Define transition probabilities for quality states (e.g., freshness, degradation).
18: **Fraud Detection and Quality Assurance:**
19: - Use CV-measured attributes (e.g., filament length, color) to detect anomalies.
20: - Compare observed data with expected probabilistic distributions.
21: - Flag deviations indicating potential fraud or quality degradation.
22: **Output:**
23: - Immutable blockchain records of sensor data and quality metrics.
24: - Real-time alerts for irregularities.
25: - Predictive insights for crop management.
26: **Repeat:**
27: - Continuously monitor and update data at predefined intervals (e.g., hourly).

(R-Pi) platforms, which serve as edge computing nodes within the system. Sensor wiring is integrated through GPIO pins and analog-to-digital converters (ADCs) where necessary, ensuring reliable data acquisition. The raw data from these sensors is transmitted in real-time to the R-Pi for preprocessing and AI-based approximation. This fusion of sensor data and CV analytics supports real-time monitoring and data-driven decision-making, optimizing farm management Fig. 3.

The actuators comprising water pumps, ventilation units and electrical controls are linked to the R-Pi's serial output ports. Based on the processed data, decisions are executed locally by the R-Pi, which sends alerts to farmers via SMS and triggers actuator responses. Farmers can also intervene manually through a connected dashboard. To ensure traceability and data integrity, sensor data and key system decisions are logged onto a Ethereum based sepolia test-net. The network uses a Proof of Authority (PoA) consensus mechanism, which is well-suited for private, permissioned environments with known validators, offering fast transaction finality. Transactions include a cryptographic nonce to prevent replay attacks and are validated through authorized node signatures. Data blocks are appended to the chain with metadata including timestamps, sensor node ID and decision logs.

4.1. Iot-blockchain integration for data traceability

The proposed model achieves robust data traceability by integrating IoT and blockchain technologies into a unified framework. Storing raw sensor-generated data directly on a public blockchain is both costly and impractical due to scalability limitations. To address this, the model processes raw sensor data at the R-Pi level, converting it into approximated actionable data before transmitting it to the blockchain. This approach optimizes resource utilization while leveraging blockchain's immutable architecture to ensure the integrity, security and traceability of agricultural information. A Python script with API-assisted functionality enables seamless integration between IoT sensors and the blockchain network. The script retrieves already processed sensor data from the R-Pi, automating the entire workflow, including data retrieval, transaction construction, signing and transmission. Every hour, the R-Pi node pro-grammatically send the processed data to a locally hosted blockchain network (sepolia test-net), ensuring consistent and reliable updates. This automation demonstrates the system's high scalability and autonomy while maintaining data integrity. By integrating these processes, the framework not only enhances traceability across the supply chain but also streamlines precision farming operations, making them more efficient and transparent.

```
1  w3 = Web3(Web3.HTTPProvider('http://127.0.0.1:8545'))
2  if not w3.is_connected():
3      print("Failed to connect to the local blockchain.")
4      exit(1)
```
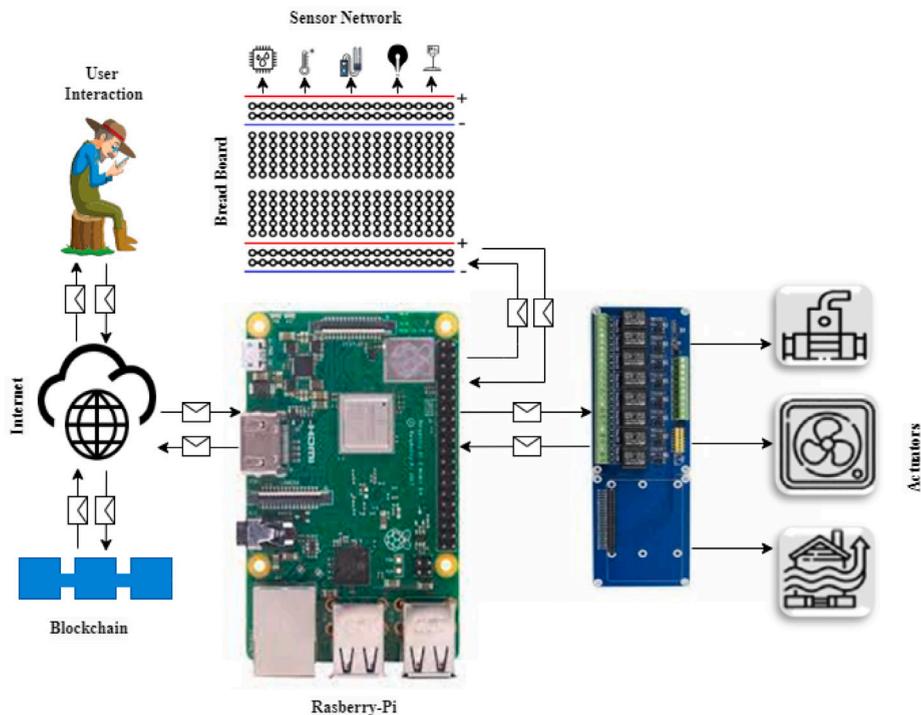
Fig. 3. Integrated framework for IoT and blockchain in precision agriculture.

```python
try:
    with open('SensorData.json') as f:
        contract_info = json.load(f)
        abi = contract_info['abi']
except FileNotFoundError:
    print("Error: SensorData.json file not found. Please check the file path.")
    exit(1)
contract_address = '0x5FbDB2315678afecb367f032d93F642f64180aa3'
contract = w3.eth.contract(address=contract_address, abi=abi)
private_key = '0xa... omissis...'
account = w3.eth.account.from_key(private_key)

def fetch_weather_data():
    try:
        weather_data = requests.get('YOUR_WEATHER_API_URL').json()
        temperature = int(weather_data['main']['temp'])
        wind_speed = int(weather_data['wind']['speed'])
        soil_moisture = int(weather_data['soil']['moisture'])
        light_intensity = int(weather_data['light']['intensity'])
        pH = int(float(weather_data['main']['pH']) * 100)
        humidity = int(weather_data['main']['humidity'])
        return temperature, wind_speed, soil_moisture, light_intensity, pH, humidity
    except Exception as e:
        print(f"Error fetching weather data: {e}")
        return None

while True:
    data = fetch_weather_data()
    if data is None:
        time.sleep(3600)
        continue
    temperature, wind_speed, soil_moisture, light_intensity, pH, humidity = data
    try:
        nonce = w3.eth.get_transaction_count(account.address)
```

```
39    tx = contract.functions.updateWeather(
40        temperature, wind_speed, soil_moisture, light_intensity, pH, humidity
41    ).buildTransaction({
42        'chainId': 4,
43        'gas': 2000000,
44        'gasPrice': w3.toWei('50', 'gwei'),
45        'nonce': nonce,})
46    signed_tx = w3.eth.account.sign_transaction(tx, private_key)
47    tx_hash = w3.eth.send_raw_transaction(signed_tx.rawTransaction)
48    print(f'Transaction sent: {tx_hash.hex()}')
49 except Exception as e:
50    print(f"Error sending transaction: {e}")
51 time.sleep(3600)
```

<div align="center">Listing 1: Python Code for Blockchain Integration</div>

Smart contracts written in Solidity form the cornerstone of the IoT-Blockchain integration, ensuring the secure recording and management of processed data on the blockchain. These contracts are designed to define and execute preconditioned agreements, enabling automated and reliable interactions between the blockchain and IoT devices. Every hour, the smart contract initiates a call for data, which is detected by the Python script running on the R-Pi. The script responds by extracting processed data from the R-Pi and transmitting it to the smart contract. Subsequently, the *updateWeather* function in the smart contract updates key sensor readings along with precise timestamps. The interaction between the Python script and the smart contract is continuous and systematic, facilitating real-time updates from R-Pi node. To enhance security and efficiency, R-Pi is assigned a unique blockchain address, enabling targeted data transmission and reliable device identification within the network. This seamless integration of off-chain data with the blockchain environment demonstrates the robustness of the proposed system, as illustrated by the following Solidity function:

```solidity
1  function updateWeather(
2      int256 _temperature,
3      uint256 _soilMoisture,
4      uint256 _lightIntensity,
5      uint256 _pH,
6      uint256 _humidity
7  ) public {
8      currentWeather = WeatherData({
9          timestamp: block.timestamp,
10         temperature: _temperature,
11         soilMoisture: _soilMoisture,
12         lightIntensity: _lightIntensity,
13         pH: _pH,
14         humidity: _humidity
15     });
16 }
```

<div align="center">Listing 2: Solidity Code for Updating Weather Data</div>

4.2. Stochastic modeling for quality control

The third contribution of this paper emphasizes the integration of CV assisted statistical modeling within the proposed IoT-Blockchain architecture for effective quality control. Agricultural products exhibit unique characteristics, such as color, acidity and size, which naturally vary depending on the crop type. As living organisms, their properties evolve over time, not only during growth in the field but also after harvest and during subsequent processing when they are incorporated into complex food products. These variations lead to spatial heterogeneity and are typically represented by probability distributions, which themselves evolve over time. Parameters such as mean, variance and kurtosis of these distributions may change and in some cases, the type of distribution may shift entirely, reflecting complex, non-parametric transformations. Stochastic modeling effectively captures the temporal evolution of these dynamic characteristics by framing them as probabilistic transitions over time. This approach models the future states of agricultural products as part of a stochastic process, defined as a family of random variables:

$$\{X(t) : t \in T\}$$

Where $X(t)$ represents the state of the process at time t and T denotes the set of time indices (e.g. all times within a continuous interval or a series of discrete time points).
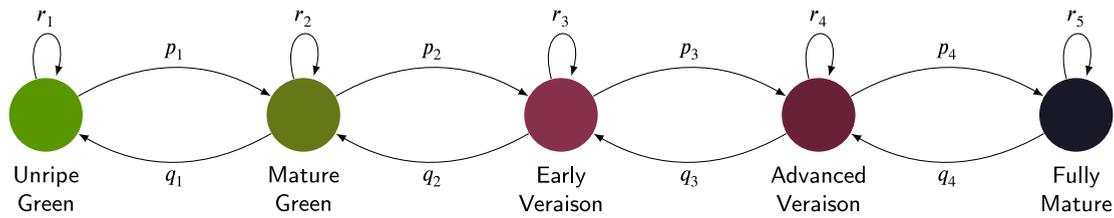
Fig. 4. Markov Chain Model of Olive Maturation.

4.2.1. Markov chain product degradation modeling

To model the natural degradation and variability in agricultural product characteristics, we use a Markov chain framework [45], which is especially effective for capturing the time-dependent, probabilistic evolution of product states [46]. Each state in the Markov chain represents a specific quality level of the product, such as levels of freshness or degradation. Transitions between these states occur according to predefined probabilities, often trending towards progressively mature or degraded states, in line with the natural life-cycle of agricultural products. However, backward transitions can also occur, representing factors like environmental variability or measurement error. This approach captures both continuous and discrete state transitions, allowing for a nuanced representation of agricultural product evolution. For instance, the ripening process of olives can be represented as a Markov chain, where states correspond to different ripeness levels and transition probabilities reflect the natural progression of ripening. Fig. 4 depicts the Markov chain states, visually representing olive colors at each ripeness stage, illustrating how the model tracks the natural progression.

Building on the Markov chain model for tracking product degradation, we can also apply this approach to monitor consistency and detect potential adulteration in agricultural products. By regularly sampling and measuring characteristics of a product batch over time, the Markov chain model enables comparison of observed measurements against expected probabilistic distributions. Significant deviations from these predicted parameters can serve as indicators of tampering or inconsistencies, enhancing quality assurance throughout the supply chain. This method has broad applicability across various agri-food products, allowing for quality control by aligning observed characteristics with expected stochastic patterns.

4.3. Saffron case study

To illustrate our proposed methodology, we present a case study focused on saffron, where filament length and color is measured and analyzed using computer vision techniques. Over time, saffron filaments undergo fragmentation due to mechanical fractures and degradation, leading to shifts in filament length and color distribution. This case study exemplifies the dynamic and fragile nature of agri-food products, underscoring the need for probabilistic modeling to track and predict their quality evolution.

4.3.1. Distribution and time-based degradation model

As with other living agricultural products, saffron characteristics evolve over time. In this case study, we focus on key time-sensitive features like filament length and color. Building on our prior research [47,48], we employ an image processing approach integrated with data visualization and analysis to assess saffron filament quality comprehensively. Initially, saffron filament lengths adhere to a truncated normal distribution, representing their quality at an early stage. This distribution is defined as:

$$f(x; \mu, \sigma, a, b) = \frac{1}{\sigma} \frac{\varphi(\frac{x-\mu}{\sigma})}{\Phi(\frac{b-\mu}{\sigma}) - \Phi(\frac{a-\mu}{\sigma})}$$

Where $\mu = 14$ mm is the mean, $\sigma = 5$ mm is the standard deviation while [a,b]=[3,30] mm represents the truncation limits. This formulation ensures the probabilities are normalized within the realistic range of filament lengths. However, as time progresses, the filaments become increasingly brittle due to factors such as dehydration, handling stress and environmental exposure leading to a gradual shift in their distribution. To model this degradation, we define a probabilistic 'breaking law' that characterizes the likelihood of filament breakage based on both the time (t) and the filament length (L). This law is expressed as:

$$P_{\text{break}}(t, L) = \min(1, (1 + \beta t)P_0)$$

Here P_0 represents the initial probability of breakage, while β determines the rate at which the likelihood of breakage increases over time. This model captures the increasing fragility of saffron filaments over time, as they dry, age and lose resilience. With each passing epoch, the probability of filament breakage rises, reflecting this gradual degradation. Each breakage event splits a filament into two parts and these events are grouped within distinct epochs. As a result, the number of filaments grows over time while their average length steadily decreases, simulating the cumulative impact of ongoing degradation. This simulation framework, grounded in the proposed breaking law, provides insights into the temporal dynamics of saffron quality. By establishing this model, we set a foundation for tracking and predicting quality changes, offering a systematic approach for monitoring fragile agricultural products like saffron throughout their life-cycle Fig. 5.

Initially, saffron filaments start with a truncated normal distribution of lengths. However, as time progresses and degradation continues, their length distribution systematically changes with each epoch of fragmentation. In each new epoch, only a subset of filaments break, causing notable shifts in the overall distribution:
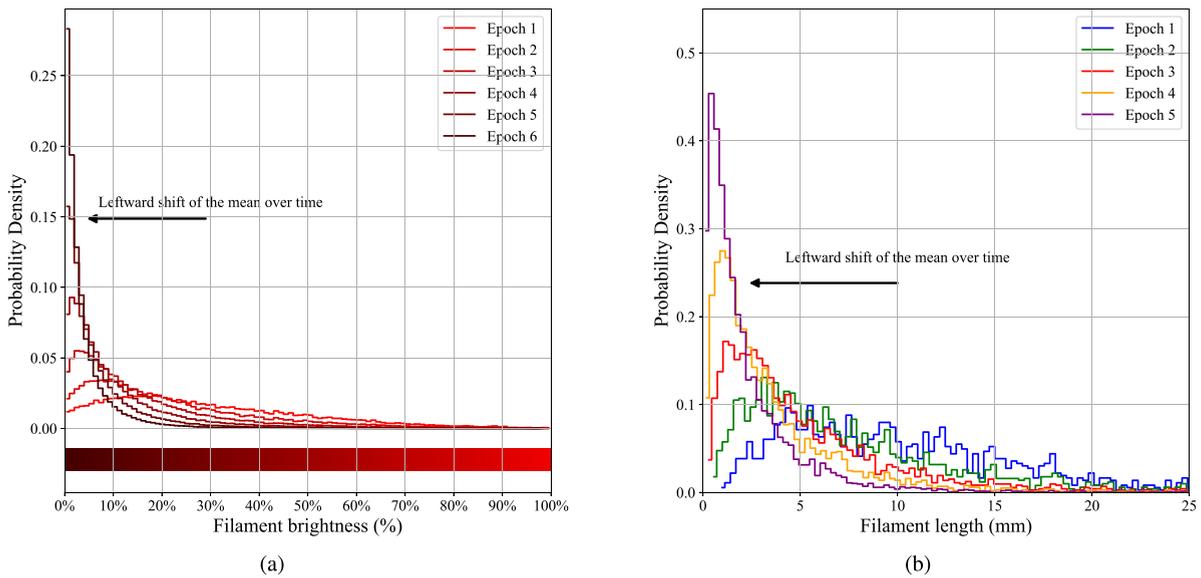
Fig. 5. Filament statistics as an estimator of quality and degradation over time, considering filament brightness (a) due to oxidation, UV, temperature and chemical degradation and length (b) due to dehidratation/mechanical stress/manipulation / transport.

- **Increase in Filament Count**: Each broken filament splits into two new fragments, leading to a growing population of shorter filaments.
- **Decrease in Average Length**: The average filament length decreases as each break results in two shorter fragments.
- **Reduction in Variance**: As more filaments break, the distribution of lengths becomes concentrated around shorter values, reducing the overall variance.

In the early epochs, the breaking process results in a bimodal distribution: some filaments remain unbroken near their original length, forming one peak, while broken filaments form another peak around shorter lengths. As this process repeats over time, the distribution becomes increasingly skewed, evolving towards a log-normal or power-law distribution. This skewed shape naturally emerges from the iterative division process, where filaments break into random, proportionate sizes. With each epoch, the probability of generating very short fragments increases, leading to an asymmetric distribution with a long tail for longer filaments but a higher concentration of shorter ones. This ongoing evolution in the filament length distribution effectively models the gradual degradation of saffron, capturing its transition from an initially uniform length to a fragmented, diverse array of shorter filaments over time.

4.3.2. Comparison with experimental data

To validate the proposed degradation model, simulated distributions were compared with experimental data derived from saffron filament measurements. The initial filament length distribution was directly sampled from experimental data, ensuring alignment between the model's starting point and real-world observations. This alignment eliminated discrepancies and enhanced the reliability of the comparative analysis. Experimental data, collected under controlled aging conditions, recorded filament length and lightness at multiple intervals to reflect natural degradation processes caused by mechanical handling, dehydration and environmental factors. Using the probabilistic 'breaking law' the simulation predicted filament breakage likelihood over time, accounting for temporal dynamics and filament variability. This approach provided a robust basis for comparison. The graphical analysis Fig. 6 revealed strong agreement between simulated and experimental data across various epochs. Both datasets initially exhibited a truncated normal distribution, representing the pristine state of saffron filaments. As degradation advanced, a clear trend of decreasing average filament length, increasing filament count and reduced variance was observed in the experimental data patterns, the simulation effectively mirrored. Intermediate stages showed bimodal distributions, with peaks corresponding to unbroken and newly broken filaments. In later stages, both datasets transitioned to skewed distributions, such as log-normal or power-law, highlighting the cumulative effects of progressive breakage events. These evolving patterns underscore the model's ability to replicate the physical dynamics of saffron degradation accurately.

Beyond filament length, lightness served as a secondary marker of quality degradation. Experimental observations showed consistent filament darkening over time, attributed to oxidation, thermal stress and chemical breakdown. While not directly tied to the breaking law, the simulation incorporated lightness trends as a complementary feature, aligning well with observed chemical and physical transformations. Minor deviations, particularly in the lower tail of the filament length distribution during later stages, likely arose from real-world factors such as filament entanglement or measurement variations not explicitly modeled. However, these deviations were negligible compared to the overall consistency between the datasets.
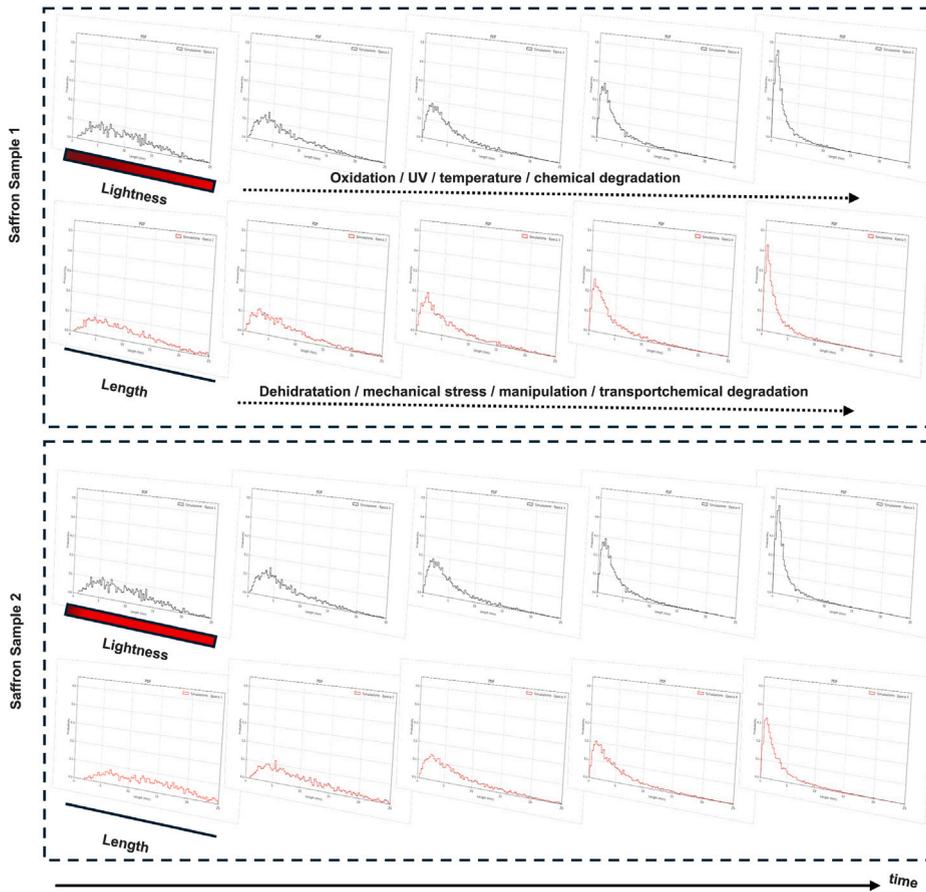
Fig. 6. Filament statistics as an identification marker of a specific saffron sample. Comparison between two lots.
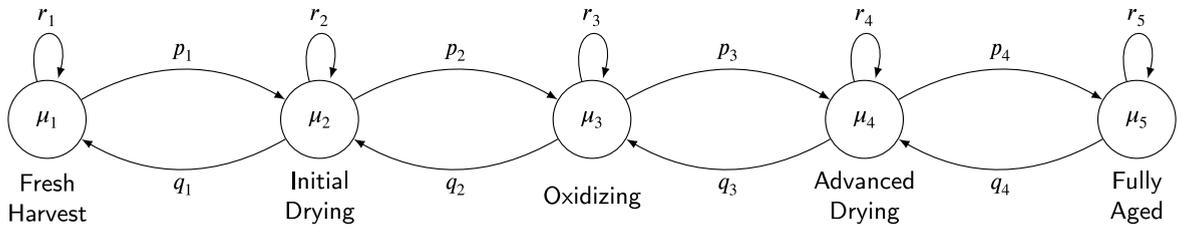

Fig. 7. Markov Chain Model for Saffron Filament Length with Average Lengths $\mu_1, \mu_2, \mu_3, \mu_4, \mu_5$.

In the ripening process of olives Fig. 4 the Markov chain framework models transitions between distinct ripeness levels, progressing from unripe green to fully mature stages. A similar methodology was employed for saffron filament degradation Fig. 7 where the states represent average filament lengths ($\mu_1, \mu_2, \mu_3, \mu_4, \mu_5$) across successive quality stages: fresh harvest, initial drying, oxidizing, advanced drying and fully aged. Transition probabilities (p1, p2, p3, p4,...) account for factors such as dehydration, mechanical stress and chemical degradation, capturing the likelihood of moving between these states. This framework effectively tracks both continuous and discrete transitions, enabling detailed modeling of time-dependent quality changes. Comparing olive ripening to saffron filament degradation highlights the Markov chain's adaptability in modeling diverse agricultural processes.

4.3.3. Blockchain-based saffron fraud detection

The integration of blockchain technology within the proposed model ensures an immutable and transparent record of saffron quality throughout its supply chain. As shown in Fig. 8, various actors contribute data to the blockchain at different stages and time points, recording key parameters of different probability distributions. These parameters, captured through computer vision, vary over time and can be used to detect potential fraud, as any unnatural changes, such as a brighter color distribution or an increase in filament length, would indicate manipulation. To enforce this, our methodology employs smart contracts that verify the statistical
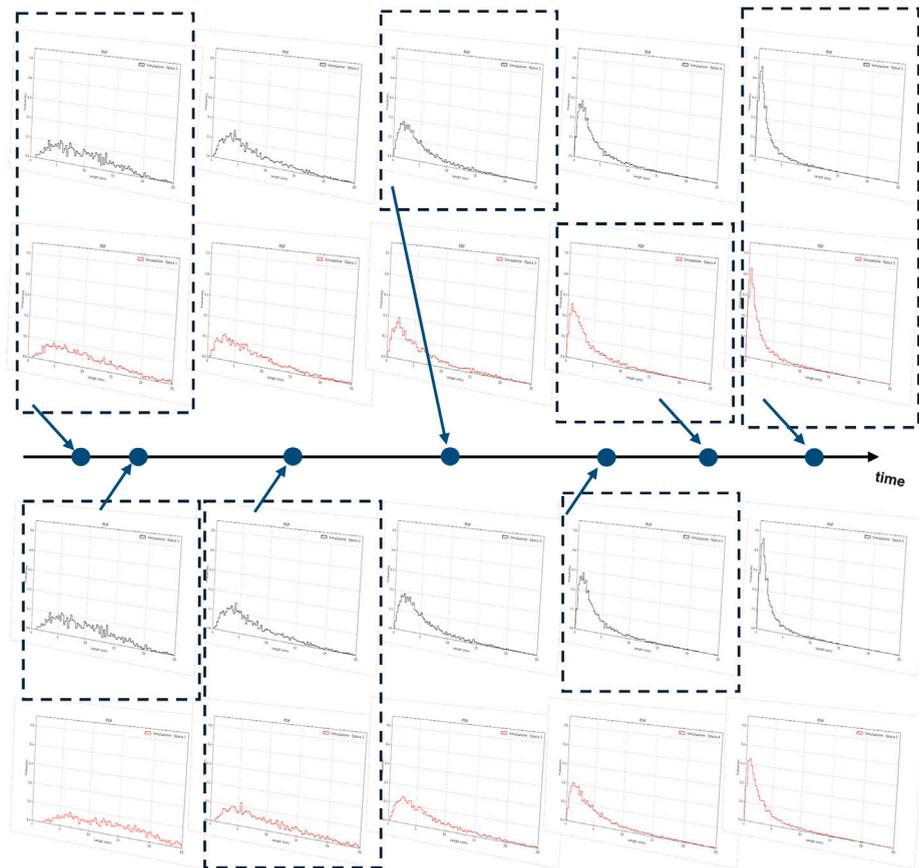
Fig. 8. Filament statistics as they are written in blocks on the blockchain.

evolution of saffron features, checking their consistency with elapsed time and lot sampling, ensuring both the integrity of the data and the authenticity of the product.

5. Discussion

The integration of CV, IoT and blockchain technologies within agricultural practices offers a novel approach to precision agriculture, which addresses numerous contemporary challenges, particularly those imposed by climate change and food security demands. In recent years, research has increasingly focused on digital solutions that enhance data security, traceability and efficiency within the agricultural sector [49]. Our study, therefore, builds upon and extends previous work by developing a novel, integrated framework that unites CV, IoT and blockchain to support real-time decision making and ensure transparent agricultural processes. The literature indicates a recent surge of interest in using these technologies to automate and optimize various agricultural operations, which aligns with the results presented in this research. As noted by [50,51], IoT and blockchain, in combination, facilitate secure data transfer and provide an immutable record of transactions that can enhance trust and accountability in precision agriculture. This intersection of technologies lays the groundwork for the future of CSA by enabling farmers to make data driven decisions that promote both productivity and sustainability.

The practical application of CV-IoT-Blockchain integration, as demonstrated in our model, is particularly relevant in high value crops such as saffron, where quality control and authenticity are crucial to both producers and consumers. Saffron, being a fragile and high cost crop, requires precise management to ensure quality and prevent counterfeiting, which has been a persistent issue in the supply chain of valuable agricultural products [52]. Our results demonstrate that the blockchain system's immutable records, combined with real time data from IoT sensors, create a trustworthy environment that can mitigate these issues. Furthermore, as our results show, the use of stochastic models like the Markov chain offers a robust approach to understanding and predicting the degradation processes of agricultural products, a finding supported by similar studies such as that of [53], which highlights the efficacy of CV in monitoring crop conditions in real-time. These findings not only advance the field of precision agriculture but also point to the potential of blockchain to revolutionize quality assurance practices within agri-food supply chains.

One of the most significant aspects of our model is its emphasis on real-time data processing and alert mechanisms. By embedding CV based analytics like AI within an IoT framework, we provide a system that can continuously monitor variables such

as temperature, soil moisture, humidity, light and pH levels. The automation of alert systems allows farmers to respond rapidly to any irregularities, thus reducing resource wastage and improving overall crop health. This capability aligns with insights from studies such as those by [54], which underscore the importance of real time monitoring for increasing agricultural efficiency. Our study adds to this body of work by incorporating blockchain technology, which ensures that all data interactions remain secure and transparent. Notably, blockchain's decentralized structure eliminates the need for third-party verification, a feature particularly advantageous in contexts where transparency and trust are critical.

A core innovation of our model lies in its use of blockchain based smart contracts for quality assurance and fraud detection. In our saffron case study, CV-measured attributes, such as filament length and color, are periodically recorded on the blockchain. Smart contracts verify that these measurements align with expected changes due to natural degradation, a feature that can detect potential tampering. Our findings correspond with those of [55], who emphasized the role of blockchain in ensuring product authenticity across agricultural value chains. By confirming that measured values match the probabilistic distributions expected over time, our model flags significant deviations that might indicate counterfeiting or quality degradation. The inclusion of smart contracts, as proposed by [56], brings a new layer of verification to our model, enhancing its applicability for high-value products prone to fraud.

The relevance of our findings extends beyond saffron and can be generalized to other crops with unique quality metrics that degrade over time, such as olives, cannabis, truffles or wine grapes. The CV-based tracking of characteristics, like color and texture, ensures that quality assessments are both objective and accurate. By establishing a digital record of quality from farm to consumer, blockchain enables traceability that can reinforce consumer trust. Similar approaches have been suggested by [57] for monitoring product freshness and integrity in the perishable meat industry. However, our model's integration of IoT and stochastic modeling into this framework is a novel contribution that further improves its utility. Through the application of the Markov chain, we have effectively captured the natural degradation patterns, offering a scientific basis for quality evaluation that can be replicated across different agricultural products.

Despite the promise of these technological advancements, the model also brings attention to several challenges that require further research and development. For instance, blockchain's scalability remains a barrier, particularly as data volumes increase. This issue has been widely discussed in previous works, with [58] noting that blockchain, though secure, can be limited by data storage and transaction processing times. Our approach addresses this concern partially by storing only approximated data on the blockchain, but future studies must continue exploring hybrid approaches that combine on-chain and off-chain storage solutions. Additionally, the lack of universally accepted regulatory standards for blockchain in agriculture presents a potential hurdle for widespread adoption. Collaboration between agricultural stakeholders, technology developers and policymakers will be essential to establish clear guidelines that promote the secure, ethical use of these technologies.

Another area for future research involves improving the robustness of IoT sensors to withstand various environmental factors in field settings. Environmental variability can affect the accuracy and reliability of IoT sensor readings, a limitation also noted by [59,60]. While our model's reliance on CV-based assessments offers some resilience to these issues, integrating redundancy mechanisms or developing sensors with higher environmental resistance could further enhance the model's reliability. Furthermore, incorporating machine learning algorithms that learn from sensor and CV data over time could provide more predictive power, allowing the model to make proactive recommendations rather than simply reacting to observed changes.

In practical terms, the model proposed in this study holds significant promise for revolutionizing agricultural practices by introducing a level of automation, transparency, and data security that surpasses traditional farming systems. The real-time monitoring and decision-making capabilities enabled by IoT and CV technologies, when integrated with the immutable data integrity assured by blockchain, align closely with the objectives of CSA to optimize resource efficiency and reduce environmental impact. To enable a meaningful evaluation of the proposed framework's advantages over existing approaches, a set of five key metrics was selected for comparison, as outlined in Table 2. These metrics were carefully chosen to reflect both technical capabilities and real-world applicability. Data Integrity is essential for maintaining trustworthy records within the agricultural supply chain, and blockchain's decentralized and tamper-proof architecture directly addresses this requirement. Scalability pertains to the system's capacity to function efficiently across farms of varying sizes and technological maturity, which is crucial for large-scale deployment. Traceability is a cornerstone of modern agri-food systems, especially for quality assurance and fraud prevention, and is greatly enhanced by blockchain's transparent and immutable data structure. Computational Performance considers the balance between the security overhead introduced by blockchain operations and the need for efficient, responsive systems in field settings. Lastly, Eco-Efficiency measures the system's potential to contribute to sustainable agriculture through the intelligent use of resources, minimizing waste and environmental impact. Together, these metrics provide a comprehensive lens through which the proposed model's benefits can be assessed in comparison to traditional IoT-based and non-blockchain traceability systems.

Conclusion

This research demonstrates the transformative potential of integrating CV, IoT and blockchain technologies to advance CSA. The proposed framework addresses critical challenges in precision farming by enhancing data integrity, traceability, and real-time decision-making, while ensuring robust fraud detection and quality assurance for high-value crops like saffron. Compared to traditional IoT and non-blockchain systems, the framework excels in scalability, transparency, and eco-efficiency, as highlighted in the discussion. By automating agricultural processes and leveraging stochastic modeling for quality control, the system reduces resource waste and improves crop management. Despite challenges such as blockchain scalability and sensor robustness, this integration paves the way for sustainable, secure, and efficient agricultural practices. Future advancements, including machine learning integration and regulatory standardization, will further solidify this framework as a cornerstone of modern agriculture, capable of meeting global food demands while preserving environmental integrity.

Table 2

Comparison of proposed framework with traditional IoT and non-blockchain traceability systems.

Metric	Proposed Framework	Traditional IoT System	Non Blockchain Traceability	Justification
Data Integrity	High	Medium	Low	The proposed framework leverages blockchain's immutable ledger to ensure data integrity. Traditional IoT systems rely on centralized databases, which are prone to tampering, while non-blockchain traceability lacks robust security mechanisms.
Scalability	High	Medium	Low	The framework processes raw sensor data at the R-Pi level before blockchain integration, optimizing resource use. Traditional IoT systems face scalability issues due to centralized architectures, and non-blockchain systems lack interoperability.
Traceability	High	Low	Medium	Blockchain provides end-to-end traceability by recording all transactions immutably. Traditional IoT systems lack transparency, and non-blockchain traceability relies on manual or semi-automated logs.
Computational Performance	Medium	High	High	Blockchain operations introduce computational overhead due to consensus mechanisms. Traditional IoT and non-blockchain systems are more lightweight but lack advanced features.
Eco-Efficiency	High	High	Medium	The framework reduces resource wastage through real-time monitoring and automation. Traditional IoT systems also promote efficiency, while non-blockchain traceability often relies on less efficient manual processes.

CRediT authorship contribution statement

Sajid Safeer: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Methodology, Data curation, Conceptualization. **Pierluigi Gallo:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Cataldo Pulvento:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Chat GPT to structure sentences properly and to check grammar and spelling. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Data availability

No data was used for the research described in the article.

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