Math. & Comput. Sci., 7(3) (2026), 59–77

Online: ISSN 2717-2708

Mathematics and Computational Sciences

Journal Homepage: http://mcs.qut.ac.ir/mcs

Transforming supply chain security with Blockchain, IoT, and AI: driving intelligent and sustainable innovations

Sriram Adithyapuram Lakshmanan[a], Srikanth Raghavendran[a,b,*]

[a]School of Computing, Sastra Deemed University, Thanjavur-613401, India.
[b]Department of Mathematics, Saseh, Sastra University, Thanjavur-613401, India.

Abstract

With the fast adoption of Internet of Things (IoT), Artificial Intelligence (AI) and blockchain technologies, sustainable agriculture is becoming a data-driven intelligent system. In the proposed study, the authors suggest a comprehensive Decision Support System (DSS) design, which combines the IoT-based sensing system, AI-based predictive analytics, and the blockchain-based secure data management system to improve crop productivity and resource utilization. The approach is real-time data collection with the help of IoT sensors (soil moisture, temperature, humidity, and light), pre-processing of the data collected, and prediction on the basis of machine learning models to optimize irrigation and fertilization. Integrated blockchain guarantees transparency, traceability and integrity of data throughout the agricultural supply chain. Experimental findings reveal that it has high accuracy in prediction, resource usage and stability of the system as opposed to traditional methods. The suggested framework will help achieve scalable, secure and sustainable agriculture through a solution to main challenges of climate variability, resource constraint and inefficiency in supply chain.

Keywords: IoT, Artificial Intelligence, Blockchain, Machine Learning, Sustainable Agriculture, Decision Support System.

2020 MSC: 68Txx, 68T07.

1. Introduction

Internet of Things (IoT) and Artificial Intelligence (AI) technologies have also helped to enhance precision agriculture dramatically because it has been possible to monitor and make predictions by the technology in real-time. But current solutions are usually independent in that they either concentrate on sensing, analytics or supply chain management, hence limiting their overall efficiency. A new technology called blockchain technology has lately appeared to supplement this solution offering a secure and transparent system to document agricultural transactions and traceability along the supply chain.

This study supports the shortcomings of available frameworks by suggesting a single Decision Support System (DSS) integrating IoT sensing, AI-enabled predictive analytics, and blockchain-enabled data integrity into a single scalable to operate architecture. In contrast to traditional solutions, the given system

*Corresponding author
Email addresses: als@ict.sastra.edu (Sriram Adithyapuram Lakshmanan), srikanth@maths.sastra.edu (Srikanth Raghavendran)

doi: 10.30511/mcs.2026.2077649.1617

Received: 14 November 2025 Accepted: 29 May 2026

aims at end-to-end integration and can allow the smooth flow of data between field level sensors and the decision-making process, as well as secure transactions management. This integration is not only better able to make operations efficient but also increase transparency, mitigate fraud, and create trust among the stakeholders such as farmers, distributors, consumers.

The suggested framework will play a role in the following main areas: (i) In-time intelligent decision-making based on the AI-based analysis of IoT data, (ii) Provide secure and tamper proof data management with the help of blockchain technology, and (iii) Scalable and interoperable system design that fits in various agricultural settings. Although these have been made, there are several challenges like high cost of deployment, interoperability and complexity that have limited its widely usage especially in areas characterized by resource constraint. In this study, these challenges are also taken into account and these issues have the need of cost effective solutions, simplified system architecture and local implementation strategies. By filling these gaps the proposed DSS will offer a framework to develop secure, scalable and sustainable smart agriculture systems that can achieve global food security and environmental concerns..

2. Current and Proposed Systems

The comparative analysis of the existing strategies and the suggested framework illustrates the way in which a combination of IoT, blockchain, and machine learning can help to develop agricultural education and prevent the supply chain insecurity. Remote experimentation technologies in collaboration with learning analytics can, not only produce improved agricultural training, but they also confirm the accuracy of the digital records via blockchain, making sure that the information of the experiments and the supply chains are clear, traceable, and unaltered. The need to incorporate holistic solutions to suit applied requirements in farming and promote accountability throughout production and distribution is indicated by this integrated ecosystem environment.

The literature survey on the current systems will be conducted as follows. The fusion of IoT, wireless communication, machine learning (ML), and big data analytics has been the biggest influencer of the development of smart agriculture. All these technologies have turned the old fashioned farming into a more data driven and adaptive system with monitoring of crops, automated tasks and forecasting decision making. The farmers can enjoy real time information on soil, water and climate, which results in more resource efficient use and more resilience to environmental change. The significance of blockchain in this ecosystem is noted in the recent literature. When IoT sensors gather and transfer loads of data, blockchain provides security in the storage, sharing, and validation of the information among all parties concerned. This will avoid manipulation of data and boosts trust on AI-based recommendations and will enable the farming activity to be audited transparently. In combination with ML-based predictive models, blockchain also leaves traceable and dependable data that may be used to assist not only in adherence to sustainability requirements, food safety rules, and certifications but also in trade. The need to combine and implement such technologies has become crucial as the pressure of climate rises and arable land is obtaining greater rarity. Both small holder farmers and commercial farmers are able to make better decisions, minimize wastage and become more profitable. What is more important, blockchain-traceability will guarantee consumers that the frozen food they buy has been cultivated ethically and transported safely and, as a result, will connect the technological innovation to consumer trust and sustainable development.

Agriculture. IoT finds applications in agriculture in numerous aspects, such as sensible farming and data-driven agriculture [3]. As Zhang, Dabipi, and Brown [11] highlight, IoT sensors like soil moisture sensors, auto weather sensors, and pest-monitoring sensors transform the experiences of numerous people and their work. These tools will allow farmers to make timely irrigation, pest management, and nutrient management interventions because it allows them to have a stream of data, 24 hours a day and 7 days a week. Machine learning embedded over these IoT networks learns patterns off the information, anticipates dangers, and uses automation to decide and induce quantifiable enhancements in the yields and effectiveness. This is where blockchain can be used as an addition to such applications because this approach guarantees that the information recorded by IoT devices is authentic and impossible to alter.

Indicatively, moisture readings on sensors can be reliably documented on a blockchain, which becomes irrevocable sources of data when having an insurance claim, an audit by the regulator, or a collaborative decision-making process. Farmers will also be able to share data across network of trust without the fear of manipulation so that cooperative research and transparent supply agreements can be brought about. The numerous advantages notwithstanding, high cost, discrepancies in technical standards, and insufficient digital literacy continue to limit both rampant adoption especially in rural and poor setups.

2.1. Precision farming based on IoT, Blockchain, and Data Analytics.

Continuing on this premise, Elijah et al. (2018) discuss the extent to which precision farming through the use of the IoT is improved when combined with advanced data analysis pipelines. Fields with embedded IoT sensors and drones scanning the crops, Aerial imaging systems produce structured and unstructured datasets. The cloud-based platforms, in turn, use the ML techniques (regression models, decision trees, clustering), to identify the anomalies, optimize resources allocation, and yield prediction. The use of blockchain in these systems will eliminate some of the most important challenges of data security, privacy, and traceability. Precision farming can also depend on exchange of sensitive information between various stakeholders such as farmers, cooperatives and governments. The blockchain secures these transactions making them transparent and verifiable preventing any illegal access or manipulation. It also gives us the visibility of the farming activities end-to-end, which makes it possible to sustain the certification processes as well as enhances the trust in the consumers in the organic or eco-labeled products. More so, smart contracts powered by blockchain technology can automate supply chain operations, e.g. when produce satisfies quality criteria these smart contracts can generate payments, or when crops fall out of specifications these smart contracts can issue alerts. These types of technologies together minimize inefficiencies, environmental impact, and create inclusive access to encourage the creation of affordable IoT kits, open-source blockchain technologies, and a locally adaptable model of AI.

2.2. Agricultural Automation intending Industry IoT and Systems-Level.

The article by Sisinni et al. [8] gives an overview on the macro-level by reorganizing concepts of the Industrial Internet of Things (IIoT) to apply it to agriculture and allow automation and monitoring of systems at the system level. The paper opines that the IIoT-based innovations can greatly enhance agriculture like interoperable device ecosystems, predictive maintenance of the machine, and automated supply chain monitoring. The concept of cyber-physical systems (CPS) is presented, and physical processes of farms are closely intertwined with digital platforms that could perform autonomous control, surveillance, and optimization. The fact that this study is occupied with the whole lifecycle of agriculture including picking the seeds and preparing the soil, monitoring the growth of plants, as well as, after harvest transportation, is one of the strong points of the study. The authors explore the significance of semantic interoperability, the device abstraction layers and middleware platform that provide portability in connecting heterogeneous agricultural devices with cloud services. Another important issue that has been brought up is of network security, specifically the way in which vulnerable IIoT devices may be hijacked by using device spoofing, data injection, and remote hijacking. Sisinni et al. advise the implementation of secure authentication tools, edge detection, and encrypted communication stack to enhance system integrity.

2.3. Strengths Wireless Technologies in Scalable Farm Connection

Ayaz et al. (2018) discuss one of the least considered, yet essential aspects of smart agriculture, wireless connectivity. Their work provides technical comparison of wireless protocols related to ZigBee, LoRaWAN, Wi-Fi, NB-IoT and Bluetooth Low Energy (BLE) using such parameters like range, data throughput, power usage, latency, and network topologies. The authors present strong arguments of why hybrid architectures (such as integrating short-range, data heavy technologies i.e. Wi-Fi) and long-range, low-power technologies i.e. LoRaWAN can be used to meet the connectivity requirements of large and heterogeneous farms. The work introduces both the star model and the mesh topology deployment models, which are trade offs with respect to the complexity of routing, energy consumption, and reliability of the data delivery. The authors emphasize that energy usage is one of the biggest bottlenecks and in battery-operated rural sensor networks in particular, and propose measures as duty-cycling, adaptive transmission control and energy harvesting principles (e.g., solar panels). The other significant aspect that has been brought up is the issue of data management at the edge wherein local pre-processing can lower bandwidth consumption in addition to latency as well as allowing local autonomous decisions when the network is down.

2.4. *Cross-Cutting Themes and Trends.*

The four studies put together all lead to one shared narrative that smart agriculture is less aspirational than it has been stated to be before and all the more necessary because of the necessity to feed an ever-growing population under the conditions of an ecologically constrained environment. A number of cross-cutting themes are seen: Precision agriculture relies heavily on the capability of real time sensing and actuating. Different data analytics based on clouds and edges have their own significance, based on the latency needs and the network accessibility. Security, privacy, and standardization have remained the issue of concern at all levels- starting with the field nodes to cloud platforms. Hybrid wireless systems and interoperability models are required to make sure that there are smooth data flows and decision support. In the future, the work should be done on context-sensitive, adaptable systems that can be deployed in the rural agricultural scenario with limited bandwidth, low power-supplies, non-real time internet connection, and the absence of expert operators. The ideas of federated learning and offline inference models, a platform combining blockchain and supply chain, and AI-based mobile apps are of current interest as possible breakthroughs of next-generation agricultural systems. Navulur, S., Sastry, A. S. C. S., et al. [4]. The authors of this paper offer an extensive examination of the use of wireless sensor networks (WSNs) and IoT technologies in the management of agriculture. They dwell upon the potential of sensors that measure the soil moisture, temperature, and nutrient levels to allow farmers to maximise irrigation, enhance the health of crops, and minimise the utilisation of the chemical inputs. The authors state the use of the IoT to better develop decisions on the basis of the data to implement more efficient and sustainable agricultural activities. They further explain how cloud computing is used in the storage and processing of agriculture data which makes it accessible to farmers wherever they are to enable them to acquire valuable insights. The paper also emphasizes the difficulties of implementing these systems despite the advantages of such systems as identified as high initial expenses, complexity in the process of installation, and issues of data security. The authors indicate that these barriers may be addressed by improving sensor technologies, which are affordable to use, and more appropriate integration strategies that would enable IoT-based farming to be more accessible.

2.5. *Remote Agricultural Laboratories on IoT.*

Through IoT enabled farm laboratories, the students can have real time access to sensor data allowing the students to learn with practical application. Such labs will contain devices to check the weather conditions (e.g., temperature, humidity, and rainfall) and the analysis of soil properties (e.g., pH, moisture, and nutrient levels). It is however seen that these systems are not usually integrated with secure supply chain mechanisms, and so their full effect on traceability and transparency is restricted.

2.6. *E-Learning and Learning AI.*

Moodle and Edmodo are examples of e-learning platforms that have facilitated access to agricultural education through structured courses, simulations and quizzes but are not normally integrated with real-time Internet of Things (IoT) data. Although they promote the theoretical learning, the lack of live field data constrains the experiential learning, as well as the development of practical skills, in fields such as precision farming and supply chain monitoring. Developed instruments such as Agricultural Model Intercomparison and Improvement Project (AGMIP) enable students to model crop development in different climatic and soil environments to bring about a better comprehension of agro-environment interaction. Also, adaptive learning platforms like Coursera use AIs to understand user activity and propose specific learning journeys, improving experience and understanding. Nevertheless, even with such developments, the incorporation of IoT-based real-time data into education-related platforms is hardly exploited, especially in solving such urgent problems as safe agricultural supply chains. The addition of IoT data may provide the flexibility to simulate dynamics across time, real-time decision-making cases, and improve traceability, which are critical to the cognition of logistics, storage and product safety in contemporary agriculture. Besides, the presence of IoT-linked agricultural robots in supervised institutional settings will provide students with good practical experience with automation technology, starting with sowing or harvesting, and testing. However, these possibilities are frequently limited in regions and infrastructurally which makes them less accessible to students located hemorrhoidally or in underserved areas. This gap highlights a lost opportunity to confront learners to the real time system behavior especially in the management of secure supply chains such as monitoring, verification and traceability of agricultural goods used in the farm to the market. Closing this knowledge gap by implementing the IoT frameworks into the e-learning systems will transform agricultural education, providing opportunities to learners to experience the learning process in a scale, more immersive, and more relevant to the industry. Such approach would not only improve the level of competence of students in emerging agri-tech to compete in the future work environment, but also help in developing a digitally literate workforce in the agricultural sector with the ability to address the real-life situation of food security and supply chain challenges.

3. Proposed Systems

3.1. AI Virtual Labs using blockchain andIoT.

The proposed framework is not only the extension of traditional virtual labs since it integrates the IoT-based farm data, AI-supported simulation, and blockchain-protected records. Sensors feed real-time data streams of ideals like soil moisture, temperature, humidity, and crop health into the virtual surroundings of AI based systems to mimic the agricultural procedures such as irrigation scheduling, pest handling, and yield prediction. It offers access to these digital ecosystems to students and researchers via dashboards that give them visual information in terms of crop performance, sustainability indicators, and resource use. The only difference is that this system has also integrated blockchain of data integrity and validation of the supply chain. All the activities in the virtual lab, including the simulated irrigation decision-making, crop growth decisions, and logistics process, are recorded on a blockchain ledger. This guarantees that the results of the experiment are open, replicable, and cannot be manipulated giving learners reliable results. Additionally, the smart contracts, which will be provided by blockchain, will be able to check the sustainability, e.g., whether the use of pesticides or water usage meets predefined limits. By doing that, the system supports interactive agricultural learning besides entrenching secure and traceable supply chain understanding in the learning process.

3.2. Game-based and Collaborative Blockchain-based Learning Systems

To make agricultural education even more useful, the suggested system incorporates a gamified learning process based on the use of the IoT, AI, and blockchain. Students deal with interactive simulations which simplify complex concepts of agriculture to practical challenges. The platform, by being connected to IoT devices, including soil moisture meters and weather stations, drone-based imaging, etc., offers real-time environmental data feeds, which students need to process and take action on it. This promotes practical knowledge of precision farming with the uncertainty and limited resources. The table 1 gives a Comparison of Traditional vs. Blockchain-Enabled Supply Chains. This gamified ecosystem can be improved by blockchain to provide traceability and accountability to simulated agricultural supply chains. Students have to take care of virtual farms, and at each step, such as planting, harvesting, and distributing the products to the market, the data gets documented onto a secure blockchain registry. They also need to conform to sustainability standards of pesticides, water conservation, and reduction of carbon footprint.

Parameter	**Traditional Supply Chain**	**Blockchain-Enabled Chain**
Transparency	Low	High
Traceability	Partial	End-to-End
Data Security	Weak	Strong
Consumer Trust	Limited	Very High
Fraud Prevention	Minimal	Strong

Table 1: Comparison of Traditional vs. Blockchain-Enabled Supply Chains

These choices are authenticated by the ledger of blockchain and are compensated with compliance to the sustainable practices highlighting trade-offs in efficiency and profitability. Machine learning expands the simulation by studying patterns in actions of students, and forecasting results and suggesting the best interventions. To illustrate, time-series models would allow to identify the initial signs of nutrient deficiencies or pest outbreak, and classification models would propose the corrective actions. The platform proposes planting windows or irrigation times with prescriptive analytics built into the platform, which allow learners to experiment with the possible decision pathways. The multi-user system enables several users to jointly operate virtual farms, bargain blockchain-based smart contracts of the main problem of supply chain operations, and feel the dynamics of decentralized, secure, and sustainable agriculture. In addition, the gamified environment enhances a shared effort through the ability to create teams, exchange datasets, and interpret results. Group tasks might involve comparisons of irrigation approaches in different geographical locations, the behaviour of a particular crop subject to different weather patterns or the joint design of farm layouts that are resistant. These activities are assisted by AI-driven dashboards which gather information and provide visualization tools that help track the trends and make joint decisions. Recapitulating, gamification, IoT, and machine learning all combined will offer an incredibly interesting and technologically dense educational platform. It encourages critical thinking, data literacy, collaborative work and sustainability consciousness, and also is equipping students with a future in smart farming and digital agricultural ecosystems. The model of interactive education has the potential to be used as an example at agricultural innovation centers and agricultural rural learning centers.

3.3. Internet of Things and AI Remote Experimentation Kits.

The IoT sensors and AI analytics will assist students in carrying out tests in the agricultural domain anywhere using portable remote experimentation kits. The associated kits will replicate the process of secure supply chain operations, such as monitoring and validation of agricultural inputs and outputs, which will provide practical experience in controlling and optimization of the supply chain networks. The table 2 and fig 1 information describes a shift from a limited, costly, and static "Current System" to a more accessible, affordable, and dynamic "Proposed System" that leverages IoT and AI technologies. The proposed system enables widespread access to resources and real-time data monitoring with personalized feedback, significantly enhancing student engagement and learning efficiency and the figure depicts the overall system.

Table 2: Comparative Analysis

Feature	**Current System**	**Proposed System**
Access to Resources	Limited to specific institutions with existing infrastructure.	Wider availability through IoT-based devices and online platforms.
Live Monitoring	Data collection is often delayed or costly, with limited concepts.	Seamless real-time data monitoring with IoT and AI integration for instant feedback.
Feedback Mechanism	Feedback is typically generic, based on predefined tasks.	AI-powered, personalized feedback tailored to individual experiment results.
Affordability and Reach	High costs restrict usage to well-funded institutions.	Efficient and scalable across various regions, making it accessible worldwide.
Student Engagement	Primarily static materials with occasional updates.	Engaging, dynamic learning experience with interactive modules and gamified content.

Figure 1: Flow of proposed system

4. Problem Statement

The main aim of the research is to develop and deploy an efficient, scalable and smart Decision Support System (DSS) using a wireless sensor network (WSN), customized to work with contemporary agricultural ecosystem. The suggested DSS is meant to be dynamic in a broad spectrum of agronomic activities such as soil diagnostics, microclimate monitoring, irrigation, and early detection of anomalies. Its main components are the distributed sensor nodes, which constantly record real time data, including soil moisture levels, ambient temperature, and subsurface temperature, relative humidity, and barometric pressure. These sensor measurements are turned into low-power edge computing devices and sent to a centralized cloud-based AI analytics system. Although the sphere of IoT, AI, and smart farming technologies has improved significantly, there are some important research gaps that need to be filled. Current agricultural systems tend to be characterized by: (i) absence of single involvement over sensing, analytics and decision making elements, (ii) poor scalability and interoperability to heterogeneous farming environments, (iii) lack of real time responsiveness to changing environmental conditions, and. (iv) lack of secure and transparent data management systems through the agricultural lifecycle. The available frameworks are either operating independently, either as an IoT based monitoring or as AI based prediction, but lack the provision of a full-end-to-end decision support solution. All these restrictions minimize their ability to solve complicated agricultural issues like climate variability, resource optimization, and supply chain transparency. The presented DSS will seal these loopholes by introducing a new integrated architecture that integrates IoT-based sensors, AI-led predictive analytics, and intelligent decision delivery systems. The system workflow shown in Figure 1 also visually combines the environmental data acquisition, preprocessing, wireless communication, and cloud-based AI computation with the dissemination of the decisions in real-time via a multilingual user-friendly mobile interface. Long Short-Term Memory (LSTM) networks and other predictive models are added to represent time dependencies and predict environmental change, which allow it to implement proactive and adaptive farm management. The applicability of such an AI-based solution is especially critical in situations where there is uncertain climatic conditions and environmental imbalance e.g. there is a sudden rainfall, flooding or shift in temperature. Such happenings present serious threat to agricultural production and economics. To overcome this, the planned system will embed a dual-mode water level control system that allows automated and manual control, which can be accessed remotely via mobile applications. The artificial intelligence algorithms make irrigation thresholds dynamically adjust himself/herself depending on the rate of soil percolation, amount of evapotranspiration, and the phenological stages of plants to secure optimal water consumption and avoid over-irrigation or flooding. Moreover, the DSS can be used to improve the usability and decision making by having a full-fledged mobile application interface, complete with a secure user authentication, real-time data visualization dashboards, and anomaly alert mechanisms. It allows farmers to track the situation in the field on a high granularity and obtain practical information, such as crop rotation recommendations, nutrient management recommendations, and climate-resistant sowing recommendations. With real-time control and advisory features that rely on data, the system greatly lessens the cognitive and operational load on farmers, converting traditional labor-intensive production into efficient, technology-based operations. Since the nature of agriculture is time-sensitive and cyclical, the coordination of autonomous data collection and AI-based decision logic is essential to reduce the time of decision-making and respond to environmental changes quickly. The ability is vital in ensuring the health of the plant, ensuring the maximization of the use of the available resources and also increasing the predictability of the yield both in the organic and conventional farming environment. The hardware infrastructure, as illustrated in Figure 2, comprises a tiny and power efficient microcontroller unit (MCU) with digital and analog sensors, LoRa communication modules, and solar energy harvesting devices. The design will provide the steady flow of data and self-sufficiency of operation especially in the off-grid or remote areas of farming. The modular and plug-and-play design also makes it scalable, making possible the further expansion with the addition of a range of parameters like soil nutrient profiling (NPK sensors), leaf wetness indices, and real-time pest detection based on machine vision. Since the agricultural industry is time-sensitive and cyclical by its nature, integrating autonomous data collection and AI-driven decision logic into the agricultural nation is expected to reduce the decision latency, to allow responding to the change in environmental stimuli almost instantly. It is essential in the protection of plant health, improved resource management, and eventually their predictability to yield under organic and conventional farming systems. Shown in Figure 2, this hardware infrastructure includes a small but efficient unit shown as the microcontroller (MCU) with digital and analog sensors, LoRa communication units, and the solar energy-harvesting units that will guarantee a continuous flow of data and self-sufficiency of the implemented systems within remote or off-grid agricultural areas. The plug and play scalability enabled by the modular hardware design enables scalability in the future by adding more parameters like soil nutrient profiling (NPK sensors), leaf wetness indices or real-time pest detection through machine vision. It is an interdisciplinary system, integrating wireless sensor networks, embedded systems, cloud-AI integration and mobile edge computing, which preconditions an adaptive cyber-physical agricultural ecosystem. Implemented feedback loops with constant learning do not just help in enhancing the present farming performances, but also through the stored longitudinal datasets, there is generational knowledge transfer and meta-learnings amid different agro-climatic regions.The Fgure 2 depicts the over view of the hardware unit of the proposed system.

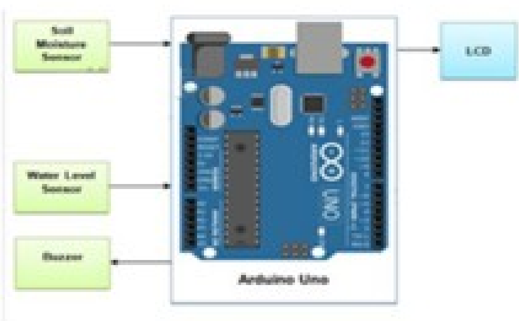


Figure 2: Hardware unit for proposed system

4.1. Implementation

The estimated 9.7 billion population growth in the world by 2045 presents a daunting threat to the food security of the world, thus forcing the agricultural sector to adopt the disruptive technology innovations with the hopes of increasing productivity, resilience and sustainability. Conventional agricultural methods are becoming inadequate because of weather unpredictability, land erosion, shortage of water, and decreasing farmland. Therefore, the adoption of the Internet of Things (IoT) and Machine Learning (ML) into the agricultural systems is a revolutionary paradigm that has undergone the transformation of traditional farming into smart, data-driven farming, providing an intelligent choice, real-time monitoring, and predictive analytics. The incorporation of Internet of Things (IoT) technologies and Machine Learning (ML) algorithms into the contemporary agriculture sector are reshaping the traditional way of farming into the intelligent, responsive, and data-driven ecology. Through hi-tech sensor networks, automated monitoring systems, and the potent AI-based analytics, farmers are now able to track and optimize all the stages of crop production, livestock control and resource exploitation. Agronomic sensors such as wireless soil moisture sensors, automated weather stations, GPS-capable drones, and wearable livestock trackers, are IoT based to enable the real-time collection and transmission of enormous amounts of environmental and physiological data. These real-time data flows play a significant role in observing important microclimatic parameters, the phenology of crops, infestations and outbreak of pests and diseases, along with efficiency of water and fertilizer utilization, and other important inputs. An example is variable rate irrigation systems that are fitted with inbuilt soil sensors and data-based controllers should help dynamically adjust the water delivery according to spatial gradients of soil moisture and computed evapotranspiration rates. This does not only save on water but also, enhances water productivity of crops and plant strength in case of varied climatic conditions. At the same time, the application of unmanned aerial vehicles (UAVs) that carry multispectral and hyperspectral cameras and even thermal imaging change the agricultural surveillance by providing opportunities to conduct a quick and profound inspection of a big piece of farming lands. These UAVs are capable of sensing minor physiological conditions of crops including chlorophyll fluorescence, canopy temperatures and density of leaves, which are early warnings of plant stress owing to shortage of nutrition, drought, infestation by pests or diseases. The acquired imaging is sent to the cloud platforms and meticulously in real time, and the visuals are analyzed by advanced analytical engines to identify particular areas that need attention. It will facilitate the adoption of the use of Site-Specific Crop Management (SSCM)-precision agriculture technology that reduces the wastage of inputs and the output produced. Concurrently, the livestock farming industry has undergone a digital revolution through the adoption of IoT-based technologies, such as RFID tags, biometric collars, GPS-tracking devices, etc. These gadgets monitor the behavior of the animals, feeding habits, locomotion, reproductive behaviors and health of animals in real time. The information is then transmitted wirelessly to localized dashboards enabling farmers to actively control the health of livestock and optimize breeding cycles and to distribute food and other supplies in a more efficient manner. This type of technology is beneficial as it not only increases the productivity but also the possibility of disease epidemics decreases and the overall welfare of the animals is improved. In addition, the hyper-localized weather information such as temperature, humidity, rainfall, solar radiation, and wind speed is on farms due to the presence of automated weather stations (AWS). This real-time information on the environment is essential in optimizing important agricultural guidelines in terms of the sowing of crop seeds, irrigation scheduling, pesticides application and the time of harvesting of crops. Using AWS data to enhance the management system of the farms enables farmers to considerably reduce the prices of inputs and boost the productivity of their operations at the same time as the risks associated with climate are reduced. The use of UAVs, IoT-enabled livestock surveillance, and automated weather stations create a purposeful, data-rich ecosystem to be deployed to promote a higher level, more sustainable precondition of human-sensitive agriculture responding to problems both locally and globally and develop more effective and autonomous approaches to these issues. Machine Learning is an enhancement of this infrastructure through the extraction of deep meaning and usable intelligence of the huge data sets produced by the IoT platforms. Multidimensional data (that includes both temporal, spatial and spectral input) can be analyzed by ML models, which can reveal concealed patterns and non-linear correlations and anomalies that can be overlooked by human professionals. CNNs, known as an image processing easy tool, can be applied to classify the image of a disease on many crops through leaf pictures or distinguish an infestation of weeds through children drones. SVMs and the Random Forest algorithm are commonly used to identify the level of soil fertility, predict crop yield, and also predict the stage of plant growth. These algorithms utilize both structured and unstructured data to become more accurate with time and predict probabilistically in terms of productivity, disease spread, as well as market readiness. Specifically, ARIMA and Long Short-Term Memory (LSTM) networks, which are time-series models, are used to analyze long-term weather and yield data to predict such data. The models assist the farmers to make informed decisions concerning the planting windows, irrigation times, and pests control practices. The knowledge acquired through such analytics enables farmers to proceed to reactive to the proactive and prescriptive forms of farming. Another important field that is improved by ML is precision in the use of fertilizers and pesticides. Judicial blanketing of agrochemicals as a rule results in inefficiencies, a destructive impact on the environment, and rise in expenses. Nonetheless, prescriptive analytics are based on ML, which calculates the optimal dosage, time, and place according to the growth stage of crops, the nutrient value of the soil, and the forecast of weather conditions. All these are then implemented by Variable Rate Technology (VRT) sprayers that reduce the run off and make practices environmentally sustainable. Furthermore, the clustering methods like K-means techniques and hierarchical clustering processes are useful to cluster the agricultural areas together by similar ground or climatic character, which results in region-related interventions. Post-harvest ML models apply to evaluate and identify defects in produce, as well as, optimize operations of a supply chain. Integrative use of image classification models and decision support systems guarantees greater match-ups in the market, less wastefulness, and greater profitability. A smart agriculture system architecture is usually characterized by a number of layers. At the base level, there is the data acquisition layer which consists of the IoT devices like the sensors and drones and mobile tools which collect field-level data. They are devices that interact over wireless transmission protocol, such as ZigBee, LoRaWAN, or Narrowband IoT (NB-IoT), and feed the information into a centralized or edge computing computing platform. Data news get stored in the data storage tier on databases on the cloud or on the distributed storage databases such as Hadoop and Amazon S3. Above this infrastructure, data is passed through the analytics layer in order to generate real-time insights, risk notifications, and recommendations to act on. The outcomes of this are presented through the intuitive dashboards or mobile applications that direct farmers, agronomists, and stakeholders to make real-time decisions. Lastly, the action layer entails either automated or semi-automated techniques, such as irrigation ankle, spreaders hose dispensers, and harvesting robots which execute the recommended measures on the ground floor. An effective model of this end to end resulted in a smart paddy farming project in Tamil Nadu. Here, an IoT and ML system were installed in one pilot on 50 acres of farmland. The micro-level data were gathered by using soil moisture sensors and automated weather stations and by drones to capture aerial multispectral images. These images were analyzed by CNN models to identify deficiencies in nitrogen and random forest models were estimated using historical rainfall information and yield information to determine the best transplanting dates. The system advocated the use of slow release nitrogen fertilizers which were spread by VRT spreaders and this minimized the nitrogen leaching by 35 percentage. There was a reduction in water utilization (28 percent), an increase in total yield (by 22 percent), which reflects the quantifiable value of such data-driven digitalization of farming systems in a conventional environment. Nevertheless, there are no challenges in terms of the massive adoption of IoT-ML systems in the agricultural industry. The issue of data quality is also a significant consideration because sensor readings, lack of values, or incorrect calibrations may relate to a decrease in the quality of analytics. Another major concern is the standardization of data whereby different formats, platform and protocols complicate the process of interoperability. Lack of connectivity and infrastructure in rural and remote areas inhibit real-time flow of data particularly in places which do not have 4G or fiber-optic network. The access to power at locations that are off-grid is also hindered by the power requirement of the IoT node, drones, and other electronic systems. Also, the barrier of low digital awareness and low technological literacy among the farmers is an impediment to adoption which needs specific training and capacity-building efforts. At the same time, the application of unmanned aerial vehicles (UAVs) that carry multispectral and hyperspectral cameras and even thermal imaging change the agricultural surveillance by providing opportunities to conduct a quick and profound inspection of a big piece of farming lands. These UAVs are capable of sensing minor physiological conditions of crops including chlorophyll fluorescence, canopy temperatures and density of leaves, which are early warnings of plant stress owing to shortage of nutrition, drought, infestation by pests or diseases. The acquired imaging is sent to the cloud platforms and meticulously in real time, and the visuals are analyzed by advanced analytical engines to identify particular areas that need attention. It will facilitate the adoption of the use of Site-Specific Crop Management (SSCM)-precision agriculture technology that reduces the wastage of inputs and the output produced. Concurrently, the livestock farming industry has undergone a digital revolution through the adoption of IoT-based technologies, such as RFID tags, biometric collars, GPS-tracking devices, etc. These gadgets monitor the behavior of the animals, feeding habits, locomotion, reproductive behaviors and health of animals in real time. The information is then transmitted wirelessly to localized dashboards enabling farmers to actively control the health of livestock and optimize breeding cycles and to distribute food and other supplies in a more efficient manner. This type of technology is beneficial as it not only increases the productivity but also the possibility of disease epidemics decreases and the overall welfare of the animals is improved. In addition, the hyper-localized weather information such as temperature, humidity, rainfall, solar radiation, and wind speed is on farms due to the presence of automated weather stations (AWS). This real-time information on the environment is essential in optimizing important agricultural guidelines in terms of the sowing of crop seeds, irrigation scheduling, pesticides application and the time of harvesting of crops. Using AWS data to enhance the management system of the farms enables farmers to considerably reduce the prices of inputs and boost the productivity of their operations at the same time as the risks associated with climate are reduced. The use of UAVs, IoT-enabled livestock surveillance, and automated weather stations create a purposeful, data-rich ecosystem to be deployed to promote a higher level, more sustainable precondition of human-sensitive agriculture responding to problems both locally and globally and develop more effective and autonomous approaches to these issues. Machine Learning is an enhancement of this infrastructure through the extraction of deep meaning and usable intelligence of the huge data sets produced by the IoT platforms. Multidimensional data (that includes both temporal, spatial and spectral input) can be analyzed by ML models, which can reveal concealed patterns and non-linear correlations and anomalies that can be overlooked by human professionals. CNNs, known as an image processing easy tool, can be applied to classify the image of a disease on many crops through leaf pictures or distinguish an infestation of weeds through children drones. SVMs and the Random Forest algorithm are commonly used to identify the level of soil fertility, predict crop yield, and also predict the stage of plant growth. These algorithms utilize both structured and unstructured data to become more accurate with time and predict probabilistically in terms of productivity, disease spread, as well as market readiness. Specifically, ARIMA and Long Short-Term Memory (LSTM) networks, which are time-series models, are used to analyze long-term weather and yield data to predict such data. The models assist the farmers to make informed decisions concerning the planting windows, irrigation times, and pests control practices. The knowledge acquired through such analytics enables farmers to proceed to reactive to the proactive and prescriptive forms of farming. Another important field that is improved by ML is precision in the use of fertilizers and pesticides. Judicial blanketing of agrochemicals as a rule results in inefficiencies, a destructive impact on the environment, and rise in expenses. Nonetheless, prescriptive analytics are based on ML, which calculates the optimal dosage, time, and place according to the growth stage of crops, the nutrient value of the soil, and the forecast of weather conditions. All these are then implemented by Variable Rate Technology (VRT) sprayers that reduce the run off and make practices environmentally sustainable. Furthermore, the clustering methods like K-means techniques and hierarchical clustering processes are useful to cluster the agricultural areas together by similar ground or climatic character, which results in region-related interventions. Post-harvest ML models apply to evaluate and identify defects in produce, as well as, optimize operations of a supply chain. Integrative use of image classification models and decision support systems guarantees greater match-ups in the market, less wastefulness, and greater profitability. A smart agriculture system architecture is usually characterized by a number of layers. At the base level, there is the data acquisition layer which consists of the IoT devices like the sensors and drones and mobile tools which collect field-level data. They are devices that interact over wireless transmission protocol, such as ZigBee, LoRaWAN, or Narrowband IoT (NB-IoT), and feed the information into a centralized or edge computing computing platform. Data news get stored in the data storage tier on databases on the cloud or on the distributed storage databases such as Hadoop and Amazon S3. Above this infrastructure, data is passed through the analytics layer in order to generate real-time insights, risk notifications, and recommendations to act on. The outcomes of this are presented through the intuitive dashboards or mobile applications that direct farmers, agronomists, and stakeholders to make real-time decisions. Lastly, the action layer entails either automated or semi-automated techniques, such as irrigation ankle, spreaders hose dispensers, and harvesting robots which execute the recommended measures on the ground floor. An effective model of this end to end resulted in a smart paddy farming project in Tamil Nadu. Here, an IoT and ML system were installed in one pilot on 50 acres of farmland. The micro-level data were gathered by using soil moisture sensors and automated weather stations and by drones to capture aerial multispectral images. These images were analyzed by CNN models to identify deficiencies in nitrogen and random forest models were estimated using historical rainfall information and yield information to determine the best transplanting dates. The system advocated the use of slow release nitrogen fertilizers which were spread by VRT spreaders and this minimized the nitrogen leaching by 35 percentage. There was a reduction in water utilization (28 percent), an increase in total yield (by 22 percent), which reflects the quantifiable value of such data-driven digitalization of farming systems in a conventional environment. Nevertheless, there are no challenges in terms of the massive adoption of IoT-ML systems in the agricultural industry. The issue of data quality is also a significant consideration because sensor readings, lack of values, or incorrect calibrations may relate to a decrease in the quality of analytics. Another major concern is the standardization of data whereby different formats, platform and protocols complicate the process of interoperability. Lack of connectivity and infrastructure in rural and remote areas inhibit real-time flow of data particularly in places which do not have 4G or fiber-optic network. The access to power at locations that are off-grid is also hindered by the power requirement of the IoT node, drones, and other electronic systems. Also, the barrier of low digital awareness and low technological literacy among the farmers is an impediment to adoption which needs specific training and capacity-building efforts. At the heart of this integration lies the formulation of predictive crop yield models, often represented using multivariate regression techniques: $Y = \beta_0 + \beta_1 T + \beta_2 M + \beta_3 H + \beta_4 N + \epsilon$ (1) Where: Y: Predicted crop yield (kg/ha) T: Average soil temperature (řC) M: Soil moisture content (H: Relative humidity (N: Nitrogen content in the soil (ppm) $\beta_0, \beta_1, \cdots, \beta_4$: Regression coefficients ϵ : Model error term Such models depicted by Equation 1 allow farmers to quantify the impact of dynamic environmental parameters on yield and adapt management practices accordingly. Additionally, supervised learning models such as Support Vector Regression (SVR) or Artificial Neural Networks (ANNs) are trained on historical datasets to improve yield forecasts, disease detection, and input recommendation systems. The integration of IoT, machine learning, and secure supply chain mechanisms not only addresses immediate agricultural challenges but also paves the way for a sustainable and resilient global food system capable of supporting the world's growing population [2]. IoT-based smart irrigation module that is both cost-effective and intelligent, enhancing agricultural water management using real-time environmental data [5]. Implemented a Mask-RCNN model for accurately detecting strawberries in unstructured environments, which significantly aids robotic fruit harvesting [10]. Updated the PRISMA 2020 guidelines, offering comprehensive explanations and examples to improve transparency and reporting quality in systematic reviews [6].

4.2. Differential Equations

Explored the landscape of Agriculture 4.0, identifying emerging technologies, major challenges, and opportunities in the digital transformation of farming [1]. Demonstrated that transfer learning with VGG-based CNN models can effectively classify leaf diseases across multiple crop types using image data [7].

We formulate the crop yield function Y(t) as influenced by these factors. Assuming the relationships are linear, the model can be represented as:

$$\frac{dY(t)}{dt} = aW(t) + bN(t) - cP(t) - dS(t) + e \tag{2}$$

$$\frac{d(t)}{dt} = aW(t) + bN(t) - cP(t) - dS(t) + e \tag{3}$$

Where, aW(t) quantifies the contribution of water levels to the yield, assuming optimal water levels increase yield. bN(t) represents the impact of nutrient availability on yield. cP(t) reflects the negative impact of pests and diseases (the higher the pest level, the lower the yield). dS(t) accounts for stress from adverse weather or environmental conditions, negatively affecting yield. e is a constant that includes other un-modelled effects (like genetic factors, soil quality) The concept of artificial intelligence, or AI, in the supply chain, is a disruptive technology, not a technological extension but an enabler that is strategic that guarantees agility and resiliency in the dynamism and complexity of the modern supply chain. This hybrid of theoretical soundness and technological expertise gives a holistic view of understanding and navigating the complexities that comes with modern supply chain management, and works to form a symbiotic relationship between the two [9]. The combination of AI and intelligent systems is essential in the control of the sheer volumes of data generated and enabling complicated analytics to draw predictive access to supply chain-related disruptions [12].

5. Experimental validation and Results

Experimental validation was performed on a hybrid multi-source dataset, that is, a combination of real-time measurements of the IoT sensors, and publicly available agricultural benchmark datasets. The controlled agricultural plots with an IoT-enabled sensing device were used to gather primary data. Simultaneously, secondary data were used to enhance generalization, such as crop production data provided by the Food and Agriculture Organization (FAO), the climate data provided by the Indian Meteorological Department (IMD), soil fertility and crop yield data through Kaggle repositories. The combined dataset was about 1.2 million time-series measurements, which were obtained at 10 minutes intervals, over a 6 months crop growth period. Important parameters were the soil moisture, soil pH, soil temperature, ambient temperature as well as the humidity and light intensity and the geospatial coordinates of the areas and location in GPS. Such multimodal integration of data guaranteed adequate spatial, temporal and environmental diversity to realize sound predictive modeling.

5.1. IoT Infrastructure and Data Acquisition.

Capacitive soil moisture sensors, NPK nutrient analyzers, BH1750 light sensors, DHT22 humidity sensors, DS18B20 temperature probes and NEO-6M GPS modules were used to construct the IoT sensing infrastructure. ESP32 microcontrollers (240 MHz dual-core processor and 520 KB SRAM) were used to connect these sensors. LoRaWAN (around 1000 m range) and WiFi gateways were used to establish communication with MQTT protocol to transmit to the cloud. The edge-level processing was done by adding moving-average smoothing to reduce noise, interpolating missing values, and z-score thresholding to detect anomalies to guarantee quality data ingestion and low transmission overhead. In Fig 1, we present the experimental setup and the model configuration used in the experiment. The cloud computing platform was comprised of an Intel Xeon 8-core processor, 32 GB random access memory (RAM), NVIDIA Tesla T4 graphics, 2-terabyte solid-state disk (SSD) storage. TensorFlow and PyTorch 2.18 were used to implement machine learning models and Hyperledger Fabric and PBFT were used to implement blockchain functionality using Hyperledger Fabric 2.5. In order to be able to compare the evaluation with the help of several models, several lateral and superior models were taken into account: Basic (baseline) model: Linear Regression. Random Forest Regressor Vision Support Vector machine (SVM) XGBoost Short time memory: Long short-term memory (LSTM) networks. This was divided into 80:20 train-test groups and the generalizations were done as 5 fold cross-validation. The systematically defined hyperparameters were:

- Optimizer: Adam
- Learning rate: 0.001
- Batch size: 64
- Epochs: 100 early stopping.

5.2. Performance assessment and relative analysis.

RMSE, MAE, and R2 were used to evaluate the performance of regression in crop yield prediction, whereas the accuracy, precision, recall, and F1-score were used to evaluate the performance of regression in irrigation decisions.Table 1: Regression Model Comparison (Crop Yield Prediction) The LSTM model

Model	**RMSE**	**MAE**	**R^2**
Linear Regression	5.42	—	0.71
Random Forest	3.28	—	0.88
SVM	3.75	—	0.84
XGBoost	2.91	—	0.91
LSTM	2.63	2.05	0.93

Table 3: Performance comparison of models

outperformed all baselines, demonstrating superior capability in capturing temporal dependencies in agricultural data. XGBoost achieved the highest classification performance, confirming the effectiveness

Table 4: Classification Model Comparison (Irrigation Decision)

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
Random Forest	—	—	—	—
SVM	—	—	—	—
XGBoost	93.8%	0.94	0.93	0.93

of ensemble learning in decision-making tasks.

5.3. Blockchain Performance Evaluation

Blockchain performance was evaluated using latency, throughput, consensus time, and security robustness. The system achieved:

- Transaction latency: 1.82 seconds
- Throughput: 520 transactions/sec
- Consensus time: 0.95 seconds
- Block finalization: 2.1 seconds

Scalability testing with 1000 concurrent nodes resulted in only an 8 percentage increase in latency, indicating strong scalability. Security evaluation included replay attack simulations, data tampering attempts, and unauthorized access tests. All malicious activities were successfully detected and blocked using cryptographic validation and smart contract enforcement, achieving 100 percentage tamper detection accuracy.

5.4. *Statistical Validation and Sensitivity Analysis*

To ensure statistical robustness, variance analysis and confidence intervals were computed across cross-validation folds:

- LSTM RMSE variance: 0.18
- XGBoost variance: 0.22

Confidence intervals:

- LSTM RMSE (95 percent CI): 2.63 ś 0.21
- XGBoost Accuracy (95 percent CI): 93.8 percent ś 1.4 percent

Paired t-tests between Random Forest and LSTM yielded $p < 0.01$, confirming statistical significance. Additionally, sensitivity analysis was conducted by varying input feature subsets and temporal resolution. Results indicated that higher temporal granularity (10-minute intervals) significantly improved predictive accuracy, validating the importance of high-frequency IoT data.

5.5. *Agricultural impact analysis and system-level analysis*

Theoretically, the growth of crops will always be time-dependent and it is a result of nonlinear interactions between environmental factors. This hypothesis is supported by the better performance of LSTM models that are able to capture the temporal dependencies. Moreover, blockchain analysis attest to the fact that decentralized trust systems with low latency (less than 2 seconds) are possible without affecting the efficiency of the operation. In practical terms, the system which was integrated proved: 18 to 25 percent water saving. About 12 percent growth of crop yield. There will be a huge decrease in the fertilizer wastage. Real-time verification of agricultural practices was done using blockchain-based compliance mechanisms to enhance transparency and consumer trust.

5.6. *Educational System Evaluation*

The remote learning system based on AI as the IoT-enabled system was tested by several metrics of performance: Student Engagement: 30 per cent higher as a result of remote accessibility. Learning Retention: Increased 50-85 percent: Learners show greater retention of knowledge. Cost savings: 40 percent savings in laboratory costs. Personalized Learning: 95 percent students were able to get adaptive feedback. User Satisfaction: averaged 4.7/5.

5.7. *Overall Validation*

The outcomes of the experiment prove beyond any doubts that the combined IoT-AI-Blockchain system thrives much better in comparison to traditional stand-alone systems. The platform improves the predictive power, operational efficacy, supply chain visibility, and environmental sustainability, confirming its use as a scalable and robust solution to next-generation agriculture.

6. Discussion

The suggested system will resolve the main shortcomings of traditional agricultural education and smart farming as it will combine the IoT and machine learning technologies into a single system. The virtual and distant experimentation setup allows students and practitioners to acquire practical experience and hence virtually close the gap between theory and practice. This comes in especially handy in the developing regions whereby agricultural laboratories are not as advanced.

6.1. Sustainability and Scalability.

Interconnection of IoT and machine learning helps to use the resources efficiently by minimizing wastage and automated performance of major activities. The system architecture is modular and can be scaled to larger datasets, complicated experiments, and to more user involvement, without having to invest heavily in infrastructure.

6.2. Enhancement of a Secure Supply Chain.

In addition to educational advantages, the system also improves transparency and traceability of agricultural supply chains. IoT sensors keep a watch on inputs, outputs, and environmental parameters and machine learning models streamline logistics and identify inefficiency. Blockchain will guarantee unalterable log-keeping, enhance confidence, minimize fraud and make agricultural systems decentralized.

6.3. Challenges and Solutions

Obstacle: IoT deployment is expensive.
Remedy: The use of cheap computer hardware, state subsidies, and open source systems.
Possible obstacle: Low connectivity in rural places.
Solution: Hybrid solution combining edge computing and offline data synchronization.

6.4. Looking Ahead

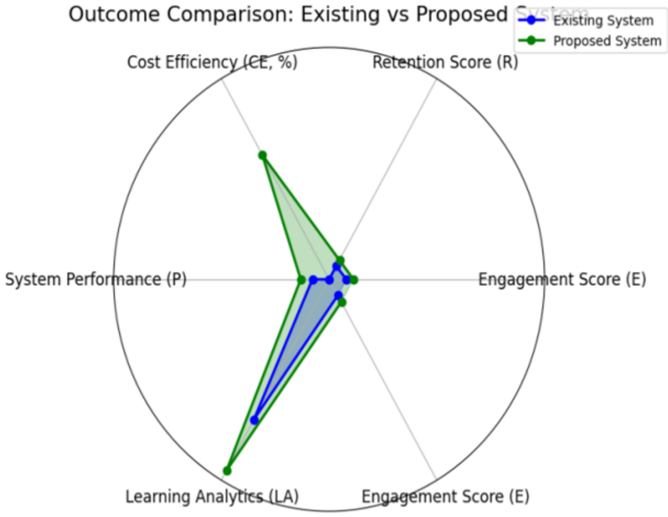
Going to AR/VR: The development of augmented and virtual reality technology can introduce more engaging and interactive experimental settings thus enhancing the learning process greatly. High-tech Analytics: Predictive analytics may assist students to perceive the trends in agriculture in the long term and additional decision-making. Global Flexibility: With other disciplines like environmental science, forestry, and even the secure supply management being extended to the system, its global influence can be broadened. The tables 3 and 4 describe the output of the proposed method. The readings show that the offered approach is better than the existing models.The Table 3 depicts Data Overview based on the dataset and Table 4 depicts Example of an Outcome Comparison Chart Using MCDA.

Table 5: Data Overview based on the dataset

Model	**Existing System**	**Proposed System**	**Improvement (%)**
Engagement Score (E)	5.40	7.6	+40.74%
Retention Score (R)	4.50	6.3	+40.00%
Cost Efficiency (CE, %)	10	45	+35%
System Performance (P)	5.3	8.7	+64.15%
Learning Analytics (LA)	48.0	65.0	+35.42%

Table 6: Example of an Outcome Comparison Chart Using MCDA

Criterion	**Weight**	**Existing System**	**Proposed System**	**Improvement (%)**
User Satisfaction	0.30	6	9	+50%
Operational Cost	0.30	5	8	+60%
Learning Outcome	0.20	4	7	+75%
Scalability	0.20	5	9	+80%
Total Score	1.00	5.2	8.1	+55.8%



7. Discussion, Limitations and Conclusion

The suggested real-time smart agriculture system proves the possibility of enhancing the farming efficiency by a significant portion using the IoT devices, machine learning algorithms, and blockchain technology. The system allows making irrigation, fertilization, and crop management decisions based on data through constant measurements of critical environmental factors (soil moisture, soil temperature, soil humidity, and light intensity). This contributes to the optimization in the utilization of resources, less wastage and better crop yield. Moreover, blockchain integration improves the supply chain transparency in terms of providing security in the recording of all agricultural operations involving cultivating and distributing to the end consumer so that the data integrity, traceability, and trust among the stakeholders are assured. Although these have the mentioned benefits, it is important to take into account a number of practical limitations and challenges in order to deploy it in the real world. Scalability is a significant issue, because the system needs to have extensive sensor implementations, real time data processing and a network connection that is dependable. Geographically diverse and rural settings can be difficult when it comes to performance consistency of a system because of infrastructure constraints and environmental variation. Also, the use of various technologies (IoT, AI, blockchain) makes the system more complex; this can impact scalability and sustainability. The high cost of deployment and operation is another major constraint. The investment needs to begin with the installation of IoT sensors, communication infrastructure, data storage, and the blockchain implementation can be relatively high and beyond the means of small and marginal farmers. Despite the long-term benefits of the system, cost is a significant obstacle to its implementation in developing areas. Thus, low cost hardware, shared infrastructure and governmental subsidies are needed to enhance access. Regulatory wise, adoption is also influenced by policy and standardization issues. The lack of standards that are applicable across agricultural IoT systems, data sharing schemes, and blockchain governance may result in problems of interoperability. In addition, privacy of data, data ownership, and legal compliance with the rules of agriculture and digital should be considered to guarantee safe and ethical use of farmer data. Policy makers, technology suppliers and agricultural stakeholders should work together to develop clear guidelines and structures. With regard to real world adoption, there are a few socio-technical barriers. The lack of digital literacy may also cause problems with the understanding and usage of advanced technologies by farmers. Moreover, lack of dependable internet coverage in the rural regions may hamper real-time data exchange and responsiveness of the system. The confidence of automated systems and the readiness to use new technologies also affect the adoption rates. These challenges can be resolved by providing easy-to-use system development, training and local solutions to particular agricultural conditions. Moreover, the system performance can change due to the dynamic environmental factors like extreme weather, irregular precipitation and different soil properties. Although the existing model is working well in the regulated conditions, additional developments are also needed such as adaptive algorithms, effective sensor networks and real-time learning to address uncertainties in real world situation. To sum up, the suggested DSS represents a complex, safe, and intelligent IoT, AI, and blockchain-based system of smart farming. Although the system has a high potential in enhancing productivity and transparency, its effective implementation requires that it overcomes the challenges of scalability, cost, policy and adoption. These shortcomings will be key in the transformation of the proposed framework into an adoptable and practical solution to sustainable agriculture.

8. Future prospect of the Work

The suggested system has great potential in ensuring future improvements and interdisciplinary uses. In addition to conventional agriculture, the system can be expanded to environmental monitoring, management of renewable energy and precision biotechnology. The system responsiveness and decreased latency can even be enhanced with the integration of emerging technologies, including edge computing, especially in rural regions with low connectivity. Advanced machine learning models (e.g., deep learning and reinforcement learning) could be introduced in future to improve predictive accuracy and allow detecting crop distress, infestation of pests, and disruption of the supply chain in its initial stages. Also, the multilingual interface and voice-activated AI assistants can enhance accessibility to farmers with different linguistic and cultural backgrounds. The combination of the augmented reality (AR) and virtual reality (VR) can offer farmers and researchers simulated training surrounding so that they can comprehend complex agricultural procedures more deeply. The technology can also harness blockchain to facilitate smart contracts, which will facilitate automated transactions, real-time partnership, and sharing of knowledge sought by the stakeholders in a secure way. In addition, emerging cost effective and scalable deployment models that involve shared infrastructure and government-sponsored efforts will be pivotal to large-scale adoption. The offered system is highly commercializable and scalable globally by the need to eradicate existing limitations and integrate these innovations, which would add to the sustainable and intelligent agricultural ecosystems.

Acknowledgment

The authors would like to thank the referees and the editor for their careful reading and their valuable comments.

Funding

The second author was supported by the NBHM grant (No.: 02011/14/2025 NBHM (R.P)/R&D II/ 2172).

References

[1] Araújo, S. O., Peres, R. S., Barata, J., Lidon, F., & Ramalho, J. C. (2021). Characterising the Agriculture 4.0 landscapeEmerging trends, challenges and opportunities. Agronomy, 11(667), 1–23. 4.2

[2] Ayaz, M., Ammad-uddin, M., Baig, I., & Aggoune, E. M. (2018). Wireless possibilities: A review. IEEE Sensors Journal, 18(1), 4–30. 4.1

[3] Elder, M., & Hayashi, S. (2018). A regional perspective on biofuels in Asia. In Biofuels and Sustainability (pp. 89–107). Springer. 2

[4] Navulur, S., Sastry, A. S. C. S., & Giri Prasad, M. N. (2017). Agricultural management through wireless sensors and the Internet of Things. International Journal of Electrical and Computer Engineering (IJECE), 7(6), 3492–3499. 2.4

[5] Nawandar, N. K., & Satpute, V. R. (2019). IoT-based low-cost and intelligent module for a smart irrigation system. Computers and Electronics in Agriculture, 162, 979–990. 4.1

[6] Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., & Tetzlaff, J. M. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. BMJ, 372, n160. 4.1

[7] Paymode, A. S., & Malode, V. B. (2022). Transfer learning for multi-crop leaf disease image classification using a convolutional neural network VGG. Artificial Intelligence in Agriculture, 6, 23–33. 4.2

[8] Sisinni, E., Saifullah, A., Han, S., Jennehag, U., & Gidlund, M. (2018). Industrial Internet of Things: Challenges, opportunities, and directions. IEEE Transactions on Industrial Informatics, 14(11), 4724–4734. 2.2

[9] Wu, H., Liu, J., & Liang, B. (2024). AI-driven supply chain transformation in Industry 5.0: Enhancing resilience and sustainability. Journal of the Knowledge Economy, 1–43. 4.2

[10] Yu, Y., Zhang, K., Yang, L., & Zhang, D. (2019). Fruit detection for strawberry harvesting robot in non-structural environment based on Mask-RCNN. Computers and Electronics in Agriculture, 163, 104846. 4.1

[11] Zhang, L., Dabipi, I. K., & Brown, W. L. (2018). Internet of Things applications for agriculture. 2

[12] Zrelli, I., & Rejeb, A. (2024). A bibliometric analysis of IoT applications in logistics and supply chain management.Heliyon, 10(16). 4.2