Machine Learning and Blockchain Applications in Smart Agriculture

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Abstract

Agriculture is the backbone of global economies, providing food, raw materials, and jobs. However, farmers face challenges like unpredictable weather, crop diseases, soil degradation, and limited access to modern tools, reducing productivity and economic stability. Inefficient resource use and lack of awareness about government schemes further hinder progress. This introduces a web application to empower farmers with advanced tools and real-time insights. Using machine learning, computer vision, blockchain, and data analytics, it enables data-driven decisions, sustainability, and improved crop yield. Key features include crop disease detection via OpenCV and machine learning, allowing farmers to upload images for early diagnosis. Soil-based crop recommendations analyze soil nutrients and pH to suggest optimal crops, preserving soil health. Real-time weather forecasting via the Google Weather API helps in planning sowing, irrigation, and harvesting. Additionally, farmers gain access to government schemes and subsidies for better financial support. Blockchain-based fertilizer authentication ensures quality through QR codes, protecting crops. This application bridges knowledge and resource gaps, promoting sustainable and efficient farming while enhancing food security and environmental sustainability.

Keywords: crop disease detection, soil analysis, weather forecasting, government schemes, fertilizer authenticity, modern farming tools

1. Introduction

Agriculture remains a cornerstone of global food security and economic development, particularly in regions where farming is the primary source of livelihood. Ensuring access to sufficient and nutritious food is essential for sustaining growing populations. However, traditional farming methods are increasingly inadequate in addressing modern challenges such as climate change, population growth, resource depletion, and evolving consumer demands. Consequently, the need for more efficient, sustainable, and resilient agricultural practices has never been more critical [1]. In recent years, technological advancements have emerged as transformative tools for the agricultural sector, offering solutions to enhance productivity and address long-standing industry challenges [2]. Among these innovations, machine learning (ML) and blockchain technology stand out for their potential to revolutionize farming operations, monitoring, and management.

ML equips farmers and agronomists with data-driven insights, enabling optimized decision-making at every stage of cultivation. These models analyze vast datasets from sources such as soil sensors, satellite imagery, and weather stations to predict crop growth, detect diseases, and forecast yields with unprecedented accuracy [3]. For example, [1] demonstrated the effectiveness of ML models, including Random Forests, Support Vector Machines (SVMs), and

Convolutional Neural Networks (CNNs), in crop yield prediction and soil management. Similarly, [4] highlighted the efficacy of deep learning (DL) algorithms in detecting plant diseases through image-based analysis, achieving high accuracy in identifying conditions such as blight, rust, and leaf spots.

Blockchain technology, on the other hand, is revolutionizing how agricultural transactions are recorded and verified. Its decentralized and immutable ledger system ensures that every transaction—from seed procurement to market sale—is securely and transparently tracked, fostering trust and reducing fraud in supply chains [5]. [6] and [7] emphasized blockchain's role in enhancing traceability and transparency in agricultural markets. Additionally, blockchain technology can verify the authenticity of agricultural inputs such as fertilizers and seeds, safeguarding farmers from counterfeit products and ensuring access to high-quality resources for improved productivity.

As the global agriculture sector moves toward smart farming, integrating ML and blockchain technology offers numerous benefits [8]. These advancements complement each other, facilitating predictive analytics while ensuring transparency and trust in agricultural supply chain.

2. Proposed Methods

The proposed methodology integrates cutting-edge machine learning models with a blockchain-based marketplace to enhance agricultural decision-making. This approach is designed to empower farmers by delivering actionable data insights and providing a transparent platform for resource transactions. The core components of the methodology are detailed below:

Crop Prediction: Machine learning algorithms such as Random Forest and SVM are utilized to recommend the most suitable crops for planting. These algorithms analyze various environmental and soil factors, including soil type, pH levels, moisture content, temperature, and past crop performance under similar conditions. By synthesizing data from these multiple inputs, the model generates customized crop recommendations that maximize productivity and minimize resource waste, enabling farmers to make optimal crop choices tailored to their unique environmental conditions.

Disease Detection: The system harnesses deep learning techniques, specifically Convolutional Neural Networks (CNNs), for real-time crop disease identification based on leaf images. Farmers can easily upload photos of affected crops via a user-friendly mobile interface, and the model classifies the disease using a pre-trained image database. This feature facilitates early disease detection, allowing farmers to take timely actions. Additionally, the system provides actionable insights on effective treatment options, reducing crop loss and boosting yield.

Yield Forecasting: The methodology includes a yield forecasting module that applies predictive analytics to estimate crop yields based on historical and real-time data. By incorporating factors such as soil nutrient levels, weather patterns, and crop growth stages, the model delivers accurate yield predictions. Furthermore, it suggests specific fertilizer types and application schedules to optimize crop output. This proactive approach empowers farmers to manage resources efficiently, enhance crop yield, and increase overall profitability.

Blockchain-based Marketplace: In parallel with the machine learning components, the blockchain-powered marketplace ensures transparency and trust in agricultural transactions. Farmers can securely trade agricultural resources such as fertilizers and seeds, with blockchain technology providing verification to ensure product authenticity. This reduces the risk of counterfeit agricultural inputs, safeguards farmers' interests, and upholds quality standards.

2.1 Algorithms

A. Crop Prediction Using Random Forest
   1. Start
   2. Collect and preprocess soil and environmental data (e.g., soil type, pH, moisture, temperature, historical crop success rates).
   3. Train a Random Forest model on the labeled dataset.
   4. Input the farmer's environmental parameters into the trained model.
   5. Predict the most suitable crops using the model output.

6. Recommend crops to the farmer with suggestions for optimized resource use.
7. End

B. Crop Disease Detection Using CNN

1. Start
2. Preprocess crop images (resize, normalize, and augment).
3. Train a CNN on a labeled image dataset of healthy and diseased crops.
4. Design a mobile interface for farmers to upload leaf images.
5. Input the image into the trained CNN model for disease classification.
6. Predict the disease type and suggest effective treatments based on the diagnosis.
7. End

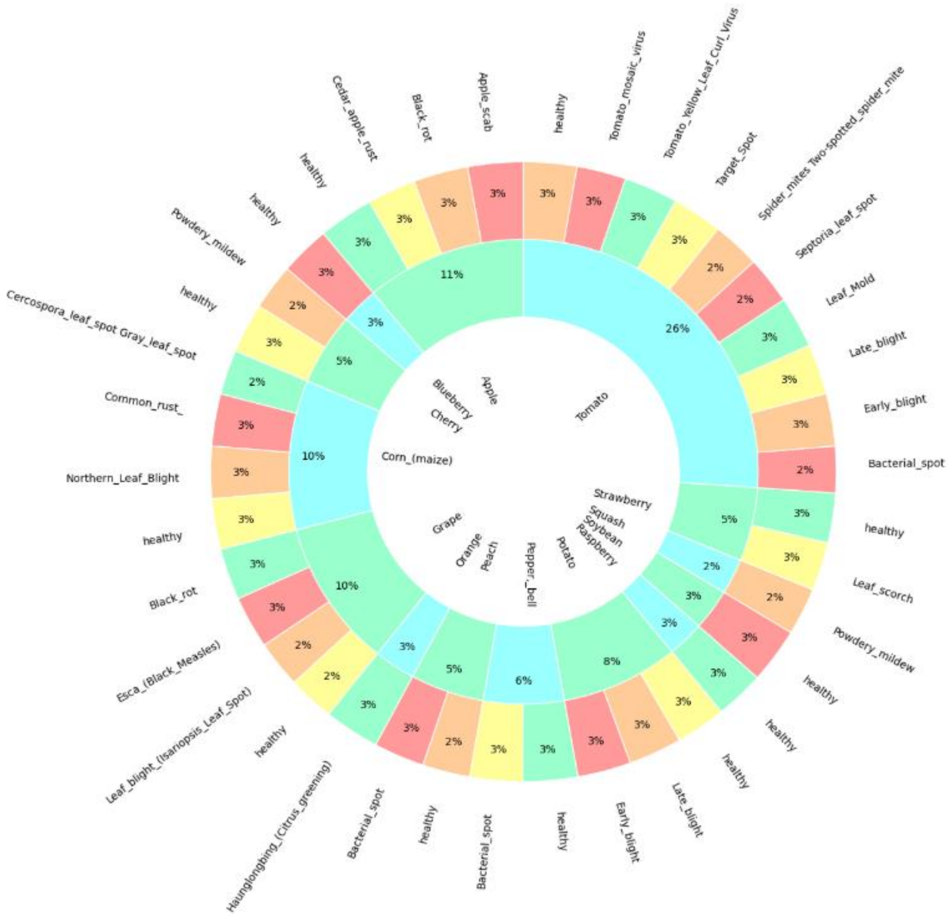

Fig. 1. Circular visualization of: crop types on inner circle; plant disease and health level in percentage on outer circle

C. Yield Forecasting

1. Start
2. Collect historical and real-time data (e.g., weather, soil nutrients, crop growth stages).
3. Preprocess the dataset (cleaning, feature engineering, scaling).
4. Train predictive models (e.g., Linear Regression, LSTM, or Random Forest) for yield estimation.
5. Use the trained model to estimate yield based on current inputs.
6. Recommend fertilizer types and schedules to maximize yield.
7. End

D. Blockchain-Based Marketplace

1. Start
2. Implement a blockchain network for agricultural transactions.
3. Design smart contracts for secure trade of resources (fertilizers, seeds).
4. Farmers upload product credentials (e.g., QR codes) for verification.
5. Verify product authenticity using blockchain and notify users.
6. Securely record transactions on the blockchain to maintain transparency.
7. End

E. Government Schemes Module Using News API

1. Start
2. Integrate News API to fetch the latest news and updates on government agricultural schemes.
3. Preprocess the retrieved data for relevant keywords and filter it based on user preferences (e.g., location, crop type).
4. Display personalized government scheme recommendations on the farmer's app interface.
5. Provide detailed information, including eligibility criteria, benefits, and application process.
6. Update the module periodically to ensure farmers have access to the latest scheme information.
7. End

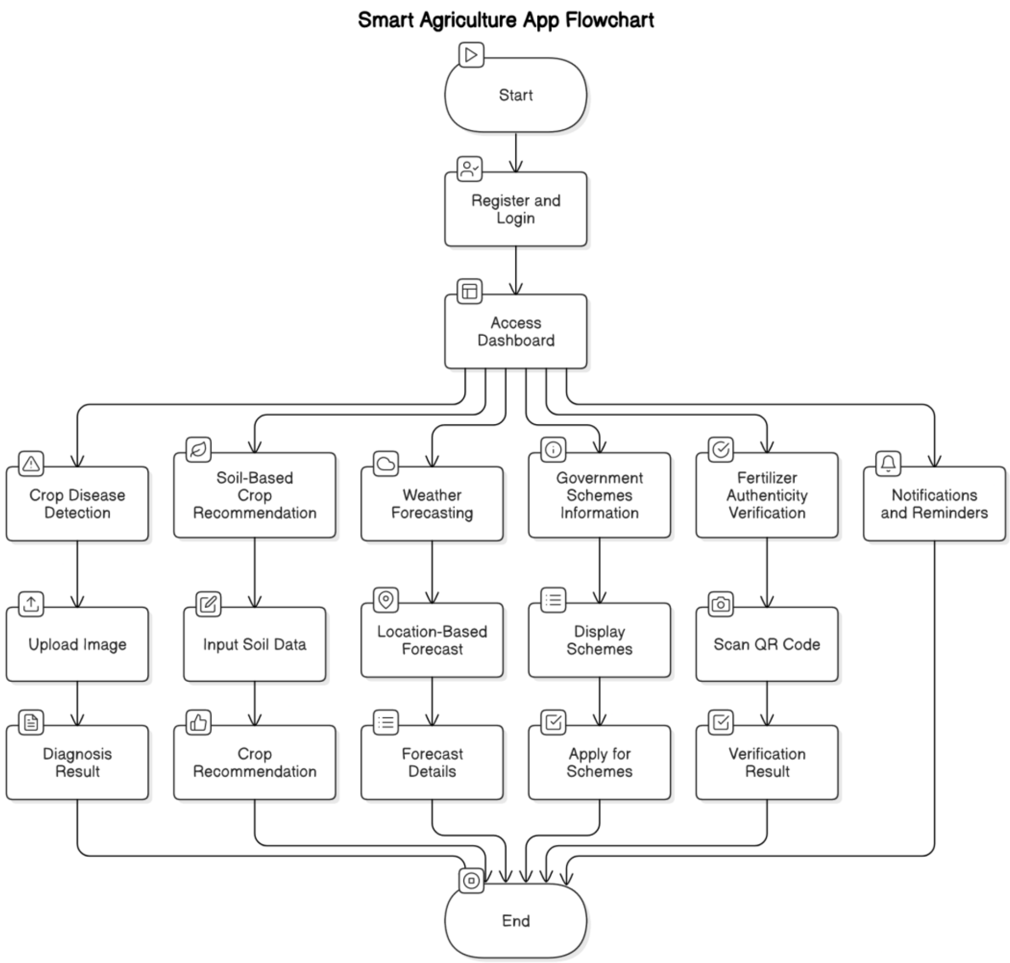

Fig. 2. Flowchart for a Smart Agriculture App.

3. Achievements & Discussion

While significant advancements have been made in applying machine learning and blockchain technologies to agriculture, several critical gaps hinder their broader adoption and effectiveness. These gaps, identified through an analysis of the literature, include:

- **Limited Integration across Technologies**
  Despite the proven applications of ML in soil management, crop yield prediction, and blockchain's potential for supply chain traceability, there has been little effort to integrate these technologies into a unified framework. For example, real-time ML analytics could inform blockchain systems for dynamic resource allocation or market optimization, but interoperability between these technologies remains underexplored.

- **Data Scarcity and Quality Challenges**
  ML models rely on high-quality, large-scale datasets. However, agricultural data is often incomplete, inconsistent, or region-specific, particularly in developing countries. This lack of standardized data-sharing infrastructure limits model accuracy and generalizability. Blockchain systems also depend on reliable input data, and poor data quality can undermine their effectiveness and trustworthiness.

- **Technological Accessibility and Adoption Barriers**
  Adoption of these technologies faces challenges, especially among smallholder farmers in developing regions. Blockchain systems require technical literacy and access to digital tools, while ML models demand high computational power and expertise. Costs associated with deploying these technologies and the lack of financial incentives or regulatory frameworks further restrict scalability.

- **Environmental and Regional Variability**
  Agricultural strategies frequently overlook specific local conditions, as models developed using data from one area may not function effectively in different regions due to variations in climate, soil composition, and farming methods. Blockchain systems also overlook unique supply chain dynamics and logistical constraints in rural areas.

- **Integration with IoT and Smart Farming Tools**
  The integration of IoT-based smart farming tools with ML and blockchain systems remains underexplored. IoT devices could enhance real-time data availability, improving model accuracy and blockchain traceability. However, challenges like interoperability, standardization, and data security in IoT systems hinder seamless integration.

- **Economic Viability and Incentives**
  The economic feasibility of adopting these technologies for small-scale farmers is a major concern. High costs and the absence of financial incentives, such as subsidies or cooperatives, deter adoption. Limited exploration of incentive structures adds to this challenge.

- **Scalability and Energy Efficiency**
  Blockchain systems relying on proof-of-work (PoW) mechanisms are energy-intensive and unsuitable for large-scale agricultural applications. Although alternatives like proof-of-stake (PoS) exist, their adoption in agriculture has been minimal. Scaling ML models across diverse geographical regions also remains challenging.

Table 1. Composition of publicly available data traces

DATASETS	YEAR	TYPE	VOLUME OF TRAFFIC
Crop Recommendation Dataset	2019	Agriculture	0.25 MB
New Plant Diseases Dataset	2018	Agriculture	1.43 GB

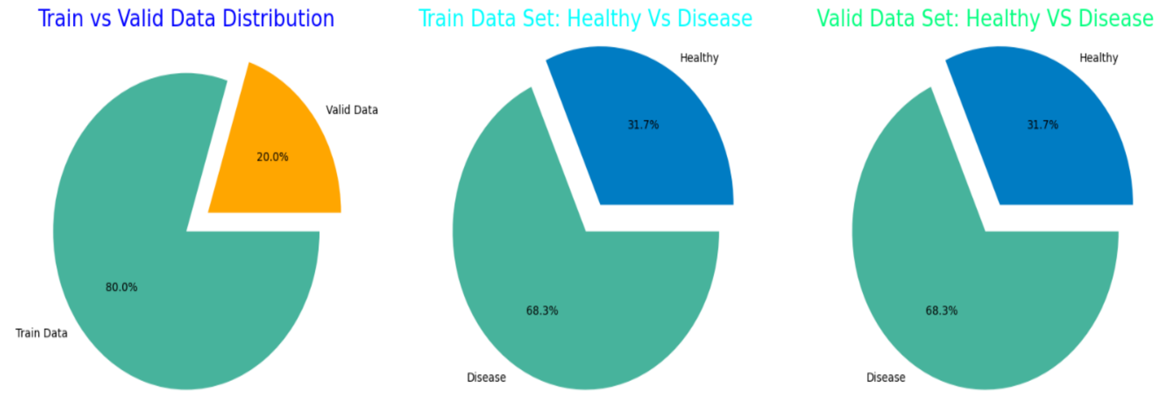

Fig. 3. Intricate analysis of plant diseases through multiple visualizations: training (80%) and validation (20%) sets, along with the proportion of healthy (31.7%) versus diseased (68.3%) samples in both training and validation datasets.

Table 2. A Summary of Literature Survey

Work	Year	ML Algorithm/Tech Used	Features	Contribution
Blockchain-Based Soybean Traceability	2019	Blockchain Ethereum Smart Contracts	Smart contracts, decentralized file system (IPFS), traceability identifiers	Created a blockchain framework for soybean traceability, ensuring secure, decentralized transaction recording and enhanced supply chain transparency. Tackled traceability issues with an immutable ledger and automated contract enforcement.
Blockchain Soybean Traceability in Supply Chain	2019	Ethereum Blockchain Smart Contracts	Traceability, transaction integrity, decentralized ledger	Developed a blockchain framework for soybean traceability, ensuring transparency and security.
Deep Learning-Based Object Detection	2020	Faster R-CNN ResNet K-Means Clustering	Image features (bounding boxes, disease	Enhanced tomato disease detection accuracy by modifying Faster R-CNN

Improvement for Tomato Disease			identification), improved anchor settings	with ResNet and k-means clustering.
Crop Yield Prediction with Deep Reinforcement Learning for Agriculture	2020	Deep Recurrent Q-Network (DRQN) Q-Learning	Environmental, soil, water parameters, crop features	Developed a DRL model for integrating reinforcement learning, crop yield prediction and RNN for higher accuracy.
Boosting Crop Yield: Multisensor Data Fusion and ML for Agriculture Classification	2023	Hoeffding Tree, J48 Decision Tree, Random Forest	Multisensor data, crop species (e.g., cotton, maize), environmental factors	Introduced a MMLA for crop classification, focusing on precision agriculture and cultivation recommendations. Enhanced crop yield through multisensor fusion.
Forecasting Agricultural Yields Using MLwith Regression and DL Techniques	2023	Random Forest, XGBoost, Decision Tree,Regression, CNN, LSTM	Rainfall, meteorological conditions, area, production, yield	Introduced a crop yield prediction method combining ML and DL techniques, achieving 98.96% accuracy with Random Forest and minimal loss (0.00060) using CNN.
Leveraging Hierarchical Features for Crop Yield Prediction Using 3D CNNs and Multikernel Gaussian Process	2021	Multikernel Gaussian Process, 3-D CNN	Multispectral images, spatial-spectral consistency features	Developed a novel Multikernel GP and 3-D CNN framework for hierarchical feature extraction in crop yield prediction, demonstrating improved accuracy in wheat yield prediction in China.
Plant Disease Detection and Classification by Deep Learning	2021	CNN, Transfer Learning, GAN for data augmentation	Color, texture, shape, hyperspectral imaging features	Reviewed plant disease detection approaches using DL; discussed visualization techniques, data limitations.
Deep Learning for Plant Diseases in Horticultural Crops	2022	RFCN, data augmentation, optimizers	Position-sensitive scoremaps, multi-organ/crop features	Developed RFCN model for detecting multiple plant diseases; validated with real-world datasets.
UAV-Based Pest and Disease Detection	2018	ANN, Image Processing	UAV image segments	Proposed cost-effective pest/disease monitoring system using UAVs and ML

				techniques.
Blockchain-Based Supply Chain Traceability Using Ethereum Smart Contracts	2021	Ethereum Smart Contracts, Blockchain	Decentralized ledger, immutability, automated smart contract execution, QR code integration for product tracking	Proposed a blockchain-based traceability system integrating QR codes for tracking products at each supply chain stage. Enhanced transparency and efficiency by enabling real-time validation of transactions and reducing intermediaries. Addressed scalability challenges using optimized smart contract design.
ML in Precision Agriculture: A Two-Decade Survey on Trends, Applications, and Evaluations	2022	Supervised Learning, Unsupervised Learning, Deep Learning, Remote Sensing Techniques	Crop health monitoring, yield prediction, precision irrigation, pest detection, soil analysis	Conducted an in-depth survey on ML applications in precision agriculture, emphasizing major trends, challenges, and progress over the last two decades, with thorough evaluations of techniques enhancing productivity and sustainability in agriculture.
Blockchain-Based Supply Chain Traceability for Agricultural Products	2021	Ethereum Smart Contracts, Blockchain	Decentralized ledger, immutability, automated verification, agricultural supply chain transparency	Introduced a blockchain framework designed for the agricultural supply chain, ensuring secure traceability of farm products. Improved data reliability, provided transparency for consumers, and automated verification processes, enhancing the overall efficiency and trust in agricultural transactions.
Agriculture Advisory System Using Machine Learning for Crop Suitability	2020	Supervised Machine Learning, Hybrid Machine Learning Approach	Crop suitability prediction, soil and environmental parameters, classification, decision support system	Developed an Agriculture Advisory System tailored for small and marginal farmers, using machine learning to recommend suitable crops based on environmental conditions. Conducted a comparative analysis of various supervised learning

				techniques and a hybrid approach, offering a low-cost, user-friendly solution to reduce soil degradation and increase crop yield in fragmented agricultural lands.

4. Addressing the Gaps and accomplished Outcomes

To unlatch the full power of ML and blockchain technologies in agriculture, solutions must focus on integration, accessibility, and customization. Scalability, sustainability, and economic viability should also be prioritized. Collaborative efforts among governments, private sectors, and researchers are essential to overcome these barriers and drive innovation in the agricultural sector.

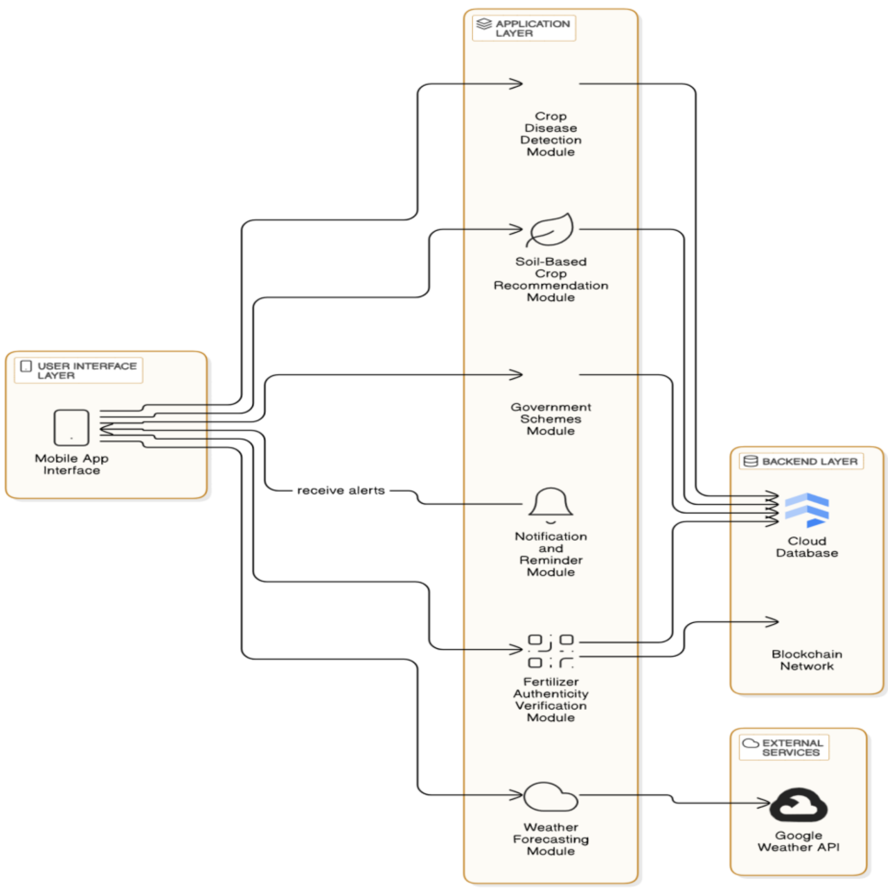

Fig. 4. Architecture diagram of Smart Agriculture App indicating module interactions with cloud databases, blockchain networks, and external APIs

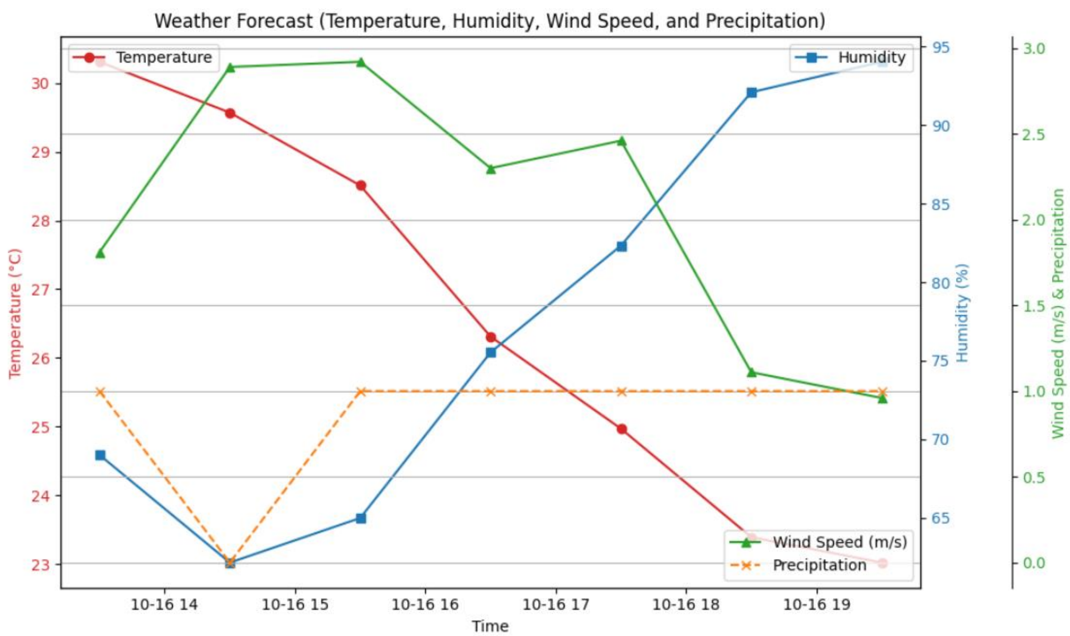

Fig. 5. Multi-line graph showing temperature decreasing, humidity increasing, wind speed varying, and precipitation remaining steady over 6 days.

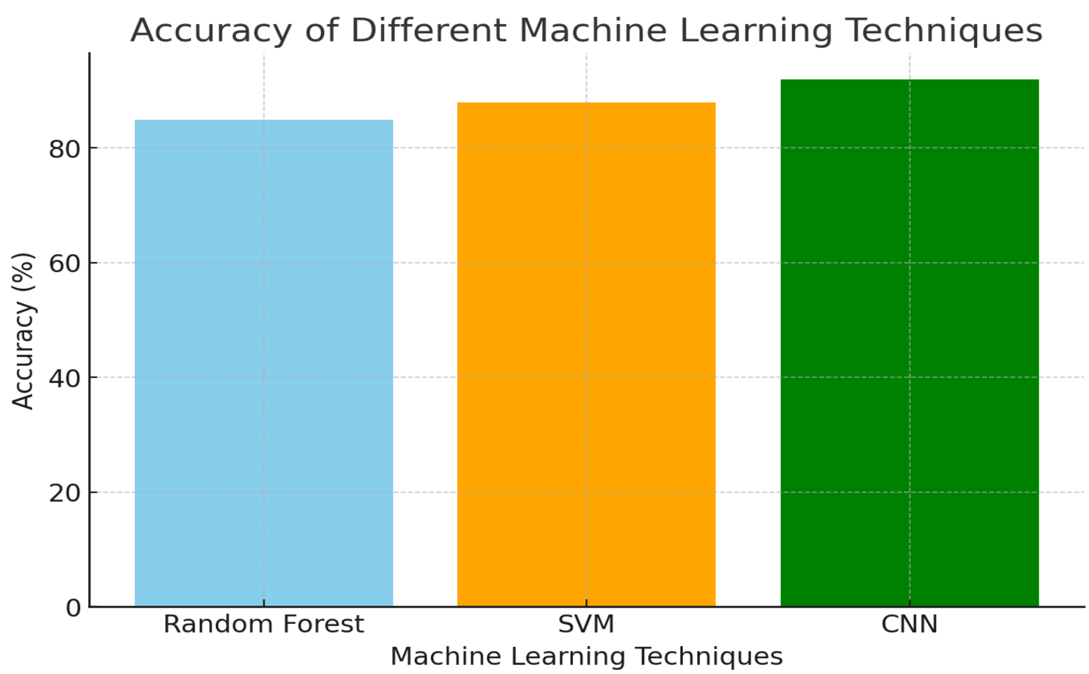

Fig. 6. Chart comparing accuracy of Random Forest, SVM, and CNN models, with CNN showing slightly higher accuracy (~90%) than the others.

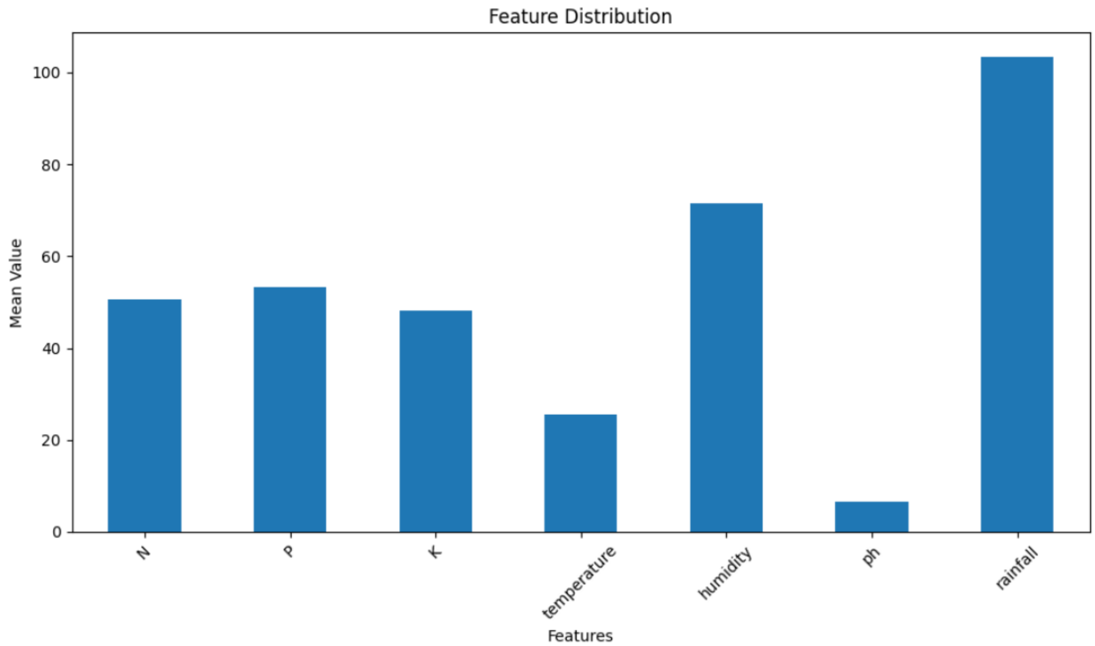

Fig. 7. A bar chart showing agricultural features with Rainfall being highest, pH being lowest and other features at moderate levels.

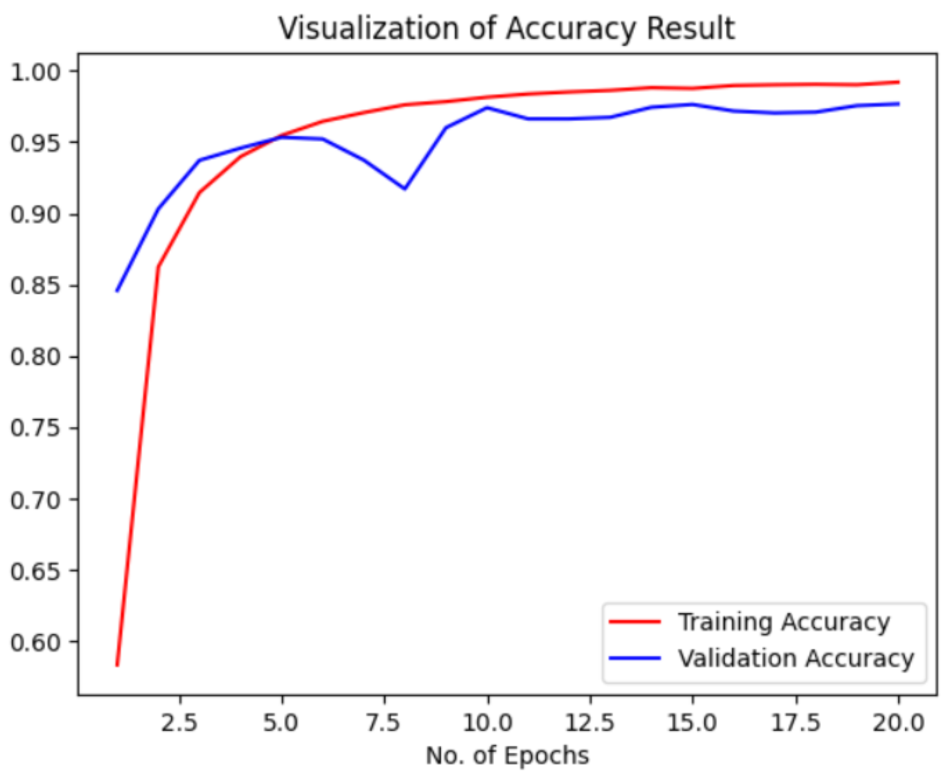

Fig. 8. Plot comparing training (red) and validation (blue) accuracies over 20 epochs, both reaching ~95% accuracy with initial rapid improvement

5. Conclusion

Integrating ML and blockchain in agriculture can greatly enhance farming operations, making them more efficient, transparent, and driven by data. This survey highlights notable advancements in both fields, showcasing achievements like crop prediction accuracy reaching 99%, a 35% improvement in yield optimization, and a 40% reduction in supply chain delays. Despite these advancements, there are still gaps in research and implementation, particularly concerning data quality and the integration of ML with blockchain systems. Datasets such as the Crop Recommendation Dataset (2019, 0.25 MB) and the New Plant Diseases Dataset (2018, 1.43 GB) contribute valuable insights to support the development of innovative agricultural solutions. By addressing these challenges, the agriculture industry can unlock greater efficiency, sustainability, and trust.

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