IoT and Machine Learning-Based Smart Agriculture: A Review

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Abstract. The rapidly developing field of "smart agriculture" harnesses artificial intelligence (AI) and machine learning (ML) to improve production, sustainability, and efficiency in the agricultural area. However, numerous obstacles to agricultural productivity exist, including various soil types, different climates, and limited access to modern farming methods. This study examines current methods for smart agriculture using ML and Internet of Things (IoT) sensors suited to the agricultural environment. Furthermore, ML and AI-powered virtual assistants can provide tailored advice on smart agricultural techniques, helping farmers make informed decisions and mitigate risks. Numerous approaches, including ML, image processing, and others, have been proposed in this context, utilizing methods such as neural networks, genetic algorithms, fuzzy logic, support vector machines, k-means clustering, k-nearest neighbour, and rough sets. Suggestions regarding the direction of future research are also enclosed with this paper.

Keywords: Smart Agriculture, Artificial Intelligence, Machine Learning, IoT sensors.

1 Introduction

Smart agriculture, or digital farming or precision agriculture, is a cutting-edge method that utilizes AI and ML technologies to enhance various aspects of agriculture. The IoT and ML based smart agriculture are widely used in agriculture to observe fields using IoT sensors such as DHT11 (a temperature and humidity sensor). Farmers can now collect and evaluate an enormous amount of data from different sources, including weather, soil moisture levels, crop growth trends, and more, thanks to ML and AI tools. In summary, ML and AI-powered smart agriculture represent a paradigm shift in modern farming. Farmers can amplify overall crop quantity and quality, cutting back their environmental impact, and optimize management of resources by utilizing IoT sensors. To ensure sustainable food production for future generations, this revolutionary technique could completely overhaul the agricultural sector. In this sense, the work is structured as follows: motivation, literature review, research gap, future directions, and conclusion.

IICTDS 2025, December 19-20, Chandigarh, India
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DOI 10.4108/eai.19-12-2025.2362537

Precision agriculture (PA) fuses IoT sensing with ML to provide field-level, data-driven decision support: what to plant, when and how much to irrigate, when and how much fertilizer/pesticide to apply, and early detection of pests/disease. The combined approach aims to increase yields, reduce input waste, and improve environmental sustainability.

2 Motivation

The critical need to address the numerous issues in the context of the agriculture sector is what drives the adoption of ML and AI in smart agriculture. Farmers may increase productivity and efficiency by optimizing their operations with ML and AI. Farmers can enhance yields while reducing labour expenses and resource consumption by automating processes such as crop monitoring, irrigation, and plant disease control. A vast amount of data can be analysed by ML and AI systems to identify potential risks and support farmers in making factual, data-driven decisions to mitigate them. Farmers may adopt sustainable farming methods such as agroforestry, organic farming, and precision farming supported by ML and AI technologies.

3 Literature Review

3.1 Challenges in Smart Agriculture

Combining datasets from different regions often requires heavy preprocessing. Low-cost Nitrogen (N), Phosphorus (P), and Potassium (K) probes can drift, leading to noisy measurements, and calibration is costly. Bandwidth or energy constraints push some systems to TinyML, but edge models are limited in capacity. Cost, farmer training, lifecycle maintenance, and trust (explainability) impede real-world uptake. Ownership of farmer data, cybersecurity, and equitable access are increasingly recognized as policy issues.

3.2 Advances in ML and IoT

Decision trees, random forests, SVM, and KNN are examples of classical supervised algorithms that are frequently used for crop categorization, soil property estimation, and basic recommender systems. Ensembles and boosting: tabular predictions (yield, nutritional status) are made using XGBoost and LightGBM. Neural networks were utilized: LSTMs/transformers for time-series forecasting (weather, yield trajectories), CNNs for image tasks (disease or weed fruit counting), and MLPs for tabular data. Hybrid pipelines: Better spatial and temporal coverage is achieved by combining in-situ sensor readings with remote-sensing picture data in multimodal models. Lightweight models used on microcontrollers to lower latency and data transfer are known as TinyML or edge ML. Recent studies investigate TinyML for on-device disease diagnosis and crop advice. The potential uses and advantages of crop recommendations that make use of IoT and ML have been the subject of numerous research projects, making this a quickly developing field of study. Table 1 below summarizes a few publications that used various AI, ML, and IoT approaches:

Table 1. Summarization of existing smart agriculture

Sl. No.	Paper reference No.	Data Set Used	Techniques Used	Tools and Sensors Used	Advantages	Issues	Accuracy
1.	[2]	Input features: Nitrogen (N), Phosphorus (P), Potassium (K), pH value of soil, Humidity (H), Temperature (T), and Rainfall.	Classical Machine Learning algorithms: Decision Trees (DT), Logistic Regression (LR), Support Vector Machine (SVM), Gaussian Naïve Bayes (GNB).	Python, Power BI (for data analysis).	1. High accuracy. 2. Simplicity of the dataset. 3. Multiple crops supported. 4. Comparison of algorithms.	1. Small dataset. 2. Static dataset. 3. No disease prediction. 4. Geographical limitation. 5. Over-fitting risk.	99.3%
2.	[4]	Input parameters: N, P, K, H, T, pH value of soil, Rainfall.	Classical Machine Learning algorithms: DT, NB, Random Forest (RF), SVM, LR Ensemble Methods: eXtreme Gradient Boosting (XGBoost).	Python.	1. High accuracy. 2. Data-driven decision making. 3. Cost-effective and scalable. 4. Wide crop coverage. 5. Improves yield and profitability. 6. Future scope.	1. Small dataset. 2. Over-fitting risk. 3. Poor SVM performance. 4. No real-time data. 5. Limited scope.	99.31%
3.	[5]	N, P, K, H, T, soil pH, Rainfall.	Classical Machine Learning algorithms: LR, SVM, DT, RF, K-Nearest Neighbor (KNN), Ensemble Methods: Bagging (BG), Extra Trees (ET), Adaptive Boosting (AdaBoost), Gradient Boosting (GB).	Python.	1. Widespread model comparison. 2. High accuracy. 3. Robust preprocessing. 4. Feature importance. 5. Practical Impact.	1. Limited dataset. 2. Generalization problem. 3. Temporal dynamics are missing. 4. Low AdaBoost performance. 5. No Real-time data.	99.30%

4.	[6]	Agriculture offices of Rayagada, Koraput, and Gajapati districts: soil minerals, soil moisture, and weather parameters.	Classical Machine Learning algorithms: LR, DT, KNN, RF, Support Vector Classifier (SVC), Ensemble methods: AB, Bagged Tree, GB, Extreme GB, Histogram GB, SGDC, Multinomial NB.	Python, Scikit-learn, Explainable AI (XAI).	1. Personalized recommendation. 2. Balanced dataset. 3. Wide comparison. 4. Android app. 5. Cloud storage. 6. High accuracy.	1. Limited districts. 2. Specificity low (0.54). 3. Sensors and drones not used. 4. Farmer adoption barrier. 5. Over-fitting risk.	100%
5.	[7]	Input parameters: N, P, K, H, T, pH value of soil, Rainfall.	Classical Machine Learning algorithms: KNN, DT, SVC, RF, Ensemble methods: Gaussian NB, ET, Light Gradient Boosting Machine (LGBM), XGBoost.	Hardware: DHT11sensor, NodeMCU (ESP8266), Arduino IDE, Software: Python, Firebase cloud platform, Kodular creator.	1. Accurate crop recommendation. 2. Farmer-friendly mobile application. 3. Cloud-based data handling. 4. Improved resource utilization. 5. Climate change is adaptable. 9. Low-cost hardware. 10. High accuracy.	1. Mobile app features are limited. 2. Dependency on the internet & cloud. 3. Sensor limitations. 4. Manual data input for some parameters like N, P, and K. 5. Regional constraints. 7. No real-time weather integration.	99%
6.	[9]	Input parameters: N, P, K, H, T, pH value of soil, Rainfall, Soil moisture.	Classical Machine Learning Algorithms: RF, DT, LR Ensemble Methods: Light GB.	Hardware: NPK Arduino, EP32, RS485, Capacitive moisture sensor. Software: Python Firebase Mobile App (Android).	1. High accuracy predictions. 2. Real-time monitoring. 3. Improved decision-making. 4. Efficient resource use. 5. Scalable system. 6. Environmental sustainability.	1. Data quality and standardization problems. 2. Power interruptions and hardware reliability issues. 4. Gap between research and practice.	98%

7.	[10]	Input parameters: N, P, K, H, T, pH value of soil, Rainfall, Soil moisture.	Classical Machine Learning algorithms: NB, RF, DT, K-NN, SVM. Ensemble Methods: XGBoost, GB.	Hardware: ESP8266 Wi-Fi, Sensors: N, P, K, pH, DHT, rainfall, Software: mobile app built with Flutter.	1. High accuracy predictions. 2. Real-time monitoring. 3. Cost-effective. 4. User-friendly mobile app. 4. Resource optimization. 5. Scalable and sustainable. 6. Local adaptation.	1. Calibration of the sensor and its accuracy. 2. Scalability. 3. Environmental variability. 4. Barriers to adoption by farmers. 5. Higher cost of IoT devices. 6. Error impact.	99.55%
8.	[12]	Input parameters: N, P, K, H, T, pH value of soil, rainfall, soil moisture, crop label.	Deep Learning algorithms: IDCSO (Improved Chicken Swarm Optimization), WLSTM (Weight-based Long Short-Term Memory), Artificial Neural Networks (ANN).	MATLAB, IoT sensors: soil moisture sensors, soil pH sensors, temperature sensors, humidity sensors, and GPS data collection for field location.	1. High accuracy. 2. Efficient feature selection. 3.IoT-Driven predictions. 4. Reduced execution time. 5. Better farmer support. 6. Handles long-term dependencies.	1. Dataset limitation. 2. Scalability problem. 3. Soil type constraints. 4. Complex model. 5. Future need.	92.68
9.	[13]	Input parameters: N, P, K, H, T, pH value of soil, Rainfall.	Classical Machine Learning algorithms: RF, SVM.	Python.	1. Not biased because it uses multiple trees on subsets of data. 2. Stable when new data is added. 3. Has a regularization parameter to avoid overfitting. 4. Kernel trick allows expert knowledge incorporation. 5. Predicts crop yield based on soil, location, and weather.	1. Small dataset size. 2. The feature set is limited (only eight variables). 3. Does not include real-world complexities such as soil moisture, sunlight, local terrain, pest conditions, or crop management practices. 4. Single region.	99.27%

					6. Recommends fertilizers crop-wise. 7. Weather info is provided using API integration.		
10.	[14]	Input parameters: N, P, K, H, T, soil pH.	Classification algorithms: DT, SVM, Gaussian NB Regression algorithms: Linear Regression, Boosting / Ensemble algorithms: RF, GB, XGBoost, Bagging, Stochastic Gradient Descent (SGD), CatBoost.	- - - - -	1. High accuracy and robust performance. 2. Balanced and enhanced dataset. 3. Considers multiple Soil and environmental factors. 4. Supports Smart Farming and integrates AI, IoT concepts, and can extend to mobile apps & chatbots. 5. Improves farmer decision-making.	1. Dataset limitations. 2. Imbalanced dataset. 3. The Boosting algorithm can overfit. 4. Lack of geographical specificity.	99.51%
11.	[15]	Input parameters: N, P, K, H, T, pH value of soil.	Machine Learning Models: LR, SVM, KNN, DT. Ensemble Techniques: Voting Classifier, Stacking Classifier.	Python.	1. Very high accuracy using optimization and an ensemble model.	1. Limiting prediction for other crops. 2. No real-time field data. 3. High correlation between P & K may impact model generalization. 4. No IoT-based real sensor integration. 5. Environmental dependency.	99.32%
12.	[17]	Features used: N, P, K, H, T, pH, rainfall.	Algorithms implemented and compared: DT, SVM, LR, GNB.	Power BI and scikit-learn.	1. Data-driven recommendations. 2. Multiple models compared.	1. The dataset is relatively small. 2. Possible overfitting. 3. No real-time integration.	99.3 %

					3. Lightweight models.	4. Important agronomic factors (soil texture, organic matter, drainage, altitude, cropping history, pests, diseases) are missing.	
13.	[20]	Input parameters: N, P, K, Soil pH, Rainfall, Humidity and Temperature.	RF, KNN, SVM.	Python.	1. Helps farmers select the best crop based on soil and climate. 2. Reduces loss due to wrong crop selection. 3. Considers multiple critical parameters (N, P, K, pH, humidity, temp, rainfall). 4. Random Forest provides high accuracy (99.22%) and fast training time. 5. The web application allows easy access for farmers. 6. Improves agricultural productivity and profit.	1. Data overlaps heavily making classification difficult; hence, simple algorithms may underperform. 2. Overfitting risk in RF if n estimators are not chosen carefully. 3. The dataset is not region-specific or real-time. 4. No integration with IoT devices. 5. The web app is simple and lacks multilingual support or farmer-oriented features.	99.22%
14.	[22]	Soil physical & chemical parameters (pH, moisture, N, P, K), climate, weather variables (temperature, rainfall, humidity), historical crop yields,	KNN, DT, SVM, NB, RF. RF, NB, Linear SVM, Random Generalized Linear Model (RGLM). ARIMA for weather forecasting, LSTM / WLSTM variants for	Sensors & hardware: DHT11, DHT22 (temp/humidity), N, P, K sensors (nitrogen, phosphorus, potassium), pH sensors (e.g., SEN-10972), soil	1. Real-time, precise recommendations when ML is combined with IoT: continuous monitoring (soil moisture, nutrients, weather) improves timeliness and relevance of	1. Implementations omit key soil nutrient variables (N, P, K) even though they are crucial; some works only used temp, humidity, pH, and rainfall. 2. Data size and generalizability: many works use	99.91%

		previous crops, and GPS location.	time-dependent predictions, and occasional reinforcement learning models for decision-making. optimization feature selection: chicken-swarm based selection, fruit-fly optimization, etc.	moisture sensors, GPS modules, Arduino Uno microcontroller, and GSM modules for connectivity. Software & platforms: Cloud-based deployments for storage and processing ML algorithms.	crop suggestions. 2. Improved prediction accuracy through ensembles and stacking. 3. Socio-economic benefits: potential to increase yields, resource efficiency (water, fertilizer), climate-adaptation support, and farmer empowerment.	relatively small datasets or restrict to a few crops, regions, limiting model generalization. 3. Computational time complexity: KNN is costly at prediction time. 4. Deployment & adoption barriers: cost of IoT deployment, farmers' training, knowledge gap, and data security, privacy concerns are noted.	
15.	[24]	N, P, K, Temperature Humidity pH, Rainfall.	Classic supervised classifiers: LR, SVM, KNN, DT, RF. Ensemble Techniques: BG, AdaBoost, GB.	Python.	1. High accuracy crop recommendations using diverse ML models. 2. Integrates soil, climate, and nutrient factors for decision-making. 3. Random Forest achieved very high accuracy, enhancing trust for farmers. 4. Helps farmers increase productivity and adapt to climate variability. 5. Scalable to different regions with similar environmental conditions. 6. Improves resource use	1. Temporal variation not fully modelled (seasonal & climate change effects). 2. Geographic generalization issues (trained on the Indian dataset may not generalize globally). 3. Limited dataset characteristics lead to: missing land quality data, static climate records and limited historical crop rotation information. 4. Validation may become optimistic if not robust.	99.31%

					efficiency: fertilizer, soil, water. 7. Supports sustainable agriculture by guiding crop rotation & soil conservation.	5. No real-time data collection.	
16.	[25]	Rainfall, Maximum temperature, Minimum temperature, Humidity, Wind speed, Cloud coverage, Bright sunshine, Cultivation area, Production amount.	Classical ML Models Investigated: SVR, NB, Ridge Regression (RR), RF Ensemble Techniques: Voting GB, Proposed Technique: K-NN, RF, RR), A blending ensemble model (2-layer ensemble).	Python (scikit-learn).	1. Higher accuracy than all classical ML and ensemble ML baselines. 2. Lower error rate (MAE, MSE, RMSE). 3. Handles nonlinearity and overfitting effectively (due to RF and RR). 4. Robust performance validated using Diebold–Mariano (DM) test. 5. Practical crop recommendation system based on predicted production and environmental thresholds.	1. The dataset includes only major crops (minor crops were excluded due to a lack of data). 2. Soil properties, market price, production cost, etc., were not included due to the difficulty of data collection. 3. Data is limited to Bangladesh only. 4. Environmental and agronomic diversity outside the region is not represented.	99%

4 Research Gap

It does not explain why a crop is recommended. It does not show feature importance or influencing parameters. It does not use LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), or rule-based interpretability. Lack of transparency reduces farmer trust and makes the model a “black box.” The paper uses only static soil values (N, P, K, pH, rainfall), which limits the reliability of predictions. Even though the system uses N, P, K values, and soil pH. Thus, nutrient information is used only for classification, not for actionable recommendations. Dataset used, image preprocessing steps, CNN or ML model architecture, accuracy of disease detection, and number of disease classes. This leaves a significant gap in the disease module. It does not include any real-time data

collection. It does not integrate sensor data (N, P, K sensors, weather APIs, etc.). It uses only manually entered values. This limits practical deployment in real farms. Real-time market price fluctuations, demand-supply trends, Risk factors (drought, floods, climate anomalies), and economic uncertainty models. Crop selection without risk analysis may mislead farmers.

5 Future Directions

This paper uses various AI, ML, and IoT techniques for smart agriculture. The authors discuss several papers' future paths in addition to their current and upcoming studies which are summarized in Table 2 below:

Table 2. Summary of the existing works over future works

Sl. No.	Paper Reference No.	Existing Work	Future Work
1.	[1]	The system already supports field mapping, crop planning, ML-based crop recommendation, CNN-based disease prediction, weather forecasting, irrigation monitoring, and input usage tracking, forming an integrated smart farming decision-support platform.	Future works include larger-scale AI adoption, tackling climate change & food demand, farmer training & skill development, integration of more automated AI tools, and enhanced real-time monitoring systems. AI is expected to transform agriculture by improving efficiency, enhancing sustainability, optimizing resource allocation, and supporting real-time monitoring.
2.	[3]	The system already uses the standard crop recommendation dataset, data preprocessing pipeline, model development, data visualization, feature selection, and system workflow.	Future requirement is to expand the dataset, integrate plant disease detection, and develop a full web & mobile application.
3.	[8]	The system uses IoT-based data collection, machine learning (KNN algorithm), and IoT–Flask server communication. Working prototype and literature support have also been achieved. .	Future needs to increase dataset size, use of advanced AI/ML models, enhanced field deployment, and potential add-ons noted in the literature.
4.	[11]	This smart farming system uses an Arduino with sensors to monitor environmental conditions, automate irrigation, and send mobile alerts. It integrates machine learning for crop recommendations and includes advanced features like hydroponics and augmented reality for improved farming support.	Future improvements focus on expanding the crop dataset with more varieties, soil types, and regional data, while enabling full automation of the irrigation system. Accuracy can be enhanced by integrating additional sensors like pH, N, P, K, light, and rainfall. The mobile app can be upgraded with alerts, data visualization, and analytics features. Incorporating AI and machine learning, including deep learning models, will support real-time recommendations, predictive irrigation, and disease detection. Finally, efforts will be made toward large-scale deployment and cost-effective implementation.
5.	[18]	The paper surveys related work using ANNs, fuzzy logic, KNN, SVMs, ensemble/stacking regression, ARMA/SARIMA/ARMAX for weather/time-series, and other crop-prediction studies. Examples	Future improvements include regularly updating datasets and automating to maintain high prediction accuracy over time. Another key enhancement is the addition of fertilizer-type

		referenced: works on forecasting crop yield using climatic parameters, KNN clustering approaches, ensemble/stacking regression for yield, ANN-based MLP predictions, and fuzzy logic combining rainfall/temperature forecasts.	recommendations by analyzing the relationship between soil conditions, climate, and available fertilizers to suggest the most suitable option for a specific crop and location. Furthermore, the system can be strengthened through more advanced automation, deeper validation of results, and expansion to cover a wider range of geographic regions.
6.	[19]	Current agricultural research shows how machine learning is becoming more and more important in enhancing farming methods and output. These include using machine learning techniques to forecast crop yield based on climate data and to sense the nitrogen status of crops. Additionally, research demonstrates the wider use of machine learning in a variety of agricultural fields, including soil analysis, crop management, animal monitoring, and water resource management. Significant research also focuses on topics including identifying plant diseases, detecting fruit ripeness, and applying machine learning techniques to advance plant biology.	Future research will concentrate on utilizing richer, more varied datasets, incorporating ML models into real-time farm management systems, and enhancing agricultural production prediction through deep learning. Additionally, it highlights integrating various data sources and investigating cutting-edge methods like clustering for improved agricultural insights.
7.	[21]	Current research emphasizes the use of several machine learning methods in agriculture and related fields. In addition to more general ML-based agricultural analytics in India, these include crop prediction using Naïve Bayes and crop yield prediction using Random Forest models. Additionally, several studies modify ideas from ensemble models used in medical diagnosis for application in agriculture. Additionally, strategies like class imbalance management and outlier handling are used to enhance model performance, and max-voting ensemble approaches are investigated for more precise disease prediction.	Future research will concentrate on enhancing the system with real-time data, integrating IoT sensors, and detecting pests and crop diseases. It also involves increasing crop coverage, taking seasonal and regional aspects into account, enhancing dataset quality using actual field data, and improving data processing utilizing sophisticated outlier techniques.
8.	[23]	The goal of current smart agriculture research is to use IoT, machine learning, and sophisticated sensing technologies to improve farming decisions. These include crop recommendation systems based on KNN, ensemble techniques, and neural networks, as well as soil quality prediction employing models like neural networks, generalized linear models, and extreme learning machines. Additionally, research investigates climatic anomaly-based soil fertility prediction, smart farming frameworks enabled by IoT and wireless sensor networks, and precision agriculture methods that employ drones, sensors, and deep learning for improved monitoring and analysis.	In order to increase forecast accuracy, future research will concentrate on growing datasets by incorporating geographical and environmental elements. It also entails using more sophisticated deep learning architectures to improve models. Large-scale IoT deployment is planned on the infrastructure side to provide more extensive data collection and monitoring. Deploying the Crop Fertility Recommendation System (CFRS) on the cloud to enable real-time usage and improved accessibility is another system-level enhancement.
9.	[26]	A variety of machine learning and deep learning techniques are used in current crop prediction and yield estimating studies to increase accuracy. These	Future research will concentrate on increasing agricultural yield prediction accuracy through the application of transfer learning and sophisticated

		include LSTM and multiple linear regression models for crop yield prediction, as well as temperature-based crop prediction utilizing polynomial regression, which achieves good performance. Major crops include wheat, rice, and maize have also been successfully predicted using RF. Furthermore, hybrid methods that combine Random Forest models with recurrent neural networks have been investigated. For precise crop recommendation and prediction tasks, multi-label classification methods utilizing ANN, KNN, and RF are also frequently employed.	deep learning algorithms. It also entails upgrading the system to provide real-time prediction using IoT devices and sensor networks, as well as assessing model performance on unbalanced datasets. Developing more computationally efficient models and enhancing model generalization through data collection from more varied regions are other important goals for speeding up and expanding the system.
10.	[27]	These methods demonstrate how machine learning is used in agriculture. ANN forecasts crop yield, KNN and ID3 rank crops, RF facilitates soil analysis, ML models evaluate water stress and offer real-time farming recommendations, and ensemble techniques and precision tools like drones and remote sensing improve crop recommendation and decision-making.	Developing web and mobile applications for farmers, offering nationwide crop recommendation services, increasing model accuracy with richer datasets, extending coverage to other crops and areas, and incorporating IoT-based real-time data for improved decision-making are the main focuses of these points.
11.	[28]	In order to increase accuracy and decision-making in agriculture, these methods concentrate on using machine learning for crop yield prediction, soil-based crop recommendation, and disease identification. They do this by utilizing techniques like ANN, KNN, SVM, DT, ensemble methods, and meteorological data. For reliable crop prediction, ensemble or hybrid models are required; a single ML algorithm is insufficient.	By combining IoT sensors for real-time data, employing big data analytics and remote sensing, integrating crop genetics, creating mobile applications for farmers, facilitating expert communication, and utilizing deep learning to increase forecast accuracy, these methods highlight contemporary smart farming.
12.	[29]	Through techniques like the Crop Selection Method for increased yield, agro-consultant systems for crop and rainfall prediction, real-time meteorological models, soil analysis using Naive Bayes and KNN, and ensemble-based precision agriculture techniques for improved decision-making, these approaches concentrate on increasing agricultural productivity.	Developing a scalable smart farming system with web deployment, incorporating yield prediction, facilitating future disease diagnosis, and enhancing decision-making through real-time weather and soil sensor data are the main goals of these points.
13.	[30]	These methods make use of cutting-edge agricultural techniques, where market-driven crop choices are supported by Apriori-based analysis and neural networks forecast corn production. SVM, LR, and DT contribute to increasing production and demand-based decision-making. Furthermore, machine learning and image processing are used to detect pests and diseases, and ontology-based systems improve crop protection tactics.	By including pest and disease diagnosis, adding pest control recommendations, expanding datasets across more regions, utilizing deep learning for improved accuracy, and eventually automating the entire farming decision-making process, these enhancements aim to improve smart farming systems.
14.	[31]	These methods show how machine learning, IoT, and remote sensing can be used in agriculture to support crop, pest, and yield prediction using techniques including ensemble methods, SVM, RF, and ANN. Real-time monitoring is made possible by smartphones and GPS-based systems, and IoT	The integration of intelligent IoT sensors to improve agricultural practices is the main emphasis of smart farming in the future. It seeks to give farmers decision support tools and automate real-time monitoring. Prediction accuracy can be greatly increased by using massive datasets.

		sensors monitor weather and soil conditions. Crop suggestions are improved by sophisticated techniques like NDVI, fuzzy logic, rough sets, and deep learning, and integrated platforms like Agromate combine these technologies for effective smart farming solutions.	Furthermore, adding more environmental factors aids in improving and increasing the accuracy of predictions. In the end, these developments will result in the creation of comprehensive smart farm automation systems, raising agricultural output and efficiency.

6 Conclusion

Each study looks at applying machine learning to estimate yield, according to this analysis. According to studies, techniques with a large number of parameters did not necessarily perform well for smart agriculture. Techniques with fewer or more parameters should be estimated to determine which performs excellently. Numerous techniques have been applied in several research projects. The findings make it impossible to determine which method is best, but all these demonstrate that a small number of ML techniques are utilized more persistently than others. The most popular models are GB, RF, LR, and NN. To determine which machine learning model performed best, most studies included a range of models. We also need to determine the extent to which DL techniques were applied for smart agriculture, since NN algorithms are widely utilized. We found that the most popular DL techniques are CNNs, LSTMs, and DNNs. We believe this paper will open new paths for investigation into smart farming.

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