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Internet of Things and Machine Learning in Smart Agriculture: A Comprehensive Review

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Abstract

Traditional farming practices in developing nations often face inefficiencies due to limited access to real-time information on soil health, weather conditions, and crop growth, resulting in reduced productivity and resource wastage. This review article summarizes smart agriculture systems that integrate the Internet of Things (IoT) and Machine Learning (ML) to enhance crop monitoring, optimize resource utilization, and support sustainable farming practices. IoT-based wireless sensor networks (WSNs) enable continuous real-time data collection on environmental and soil parameters, while ML algorithms analyze this data to support informed decision-making. The experimental results demonstrate that the proposed ensemble-based ML model achieves high predictive accuracy, validating the effectiveness of combining multiple learning algorithms for smart agriculture applications. Furthermore, real-time data updates allow farmers to respond promptly to changing field conditions, thereby minimizing losses and improving overall productivity. The integration of IoT and ML establishes a robust, data-driven agricultural framework that enhances efficiency, sustainability, and food security.

***Keywords*:** Internet of Things; Machine learning; Precision farming; Soil monitoring.

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1. Introduction

One measure of a country's economic growth is the state of its agriculture.[1] Agriculture remains the backbone of many economies, providing food, employment, and raw materials for industries. However, traditional farming practices often face challenges such as unpredictable weather, inefficient resource use, and pest infestations. In recent years, the integration of Internet of Things (IoT) technologies has revolutionized the agricultural sector by enabling real-time monitoring of soil conditions, crop health, and environmental factors.[2] Furthermore, Machine Learning (ML) enhances these systems by analyzing collected data to predict outcomes such as yield estimation, irrigation needs, and disease outbreaks, leading to smarter and more sustainable farming practices.[3] While offering fewer environmental dangers, IoT in agriculture enhances farm management, lowers waste, and boosts agricultural yields.[4] Innovations like cloud computing, radio frequency identification tags, communication between machines, sensor networks using wireless technology, and data analysis are the main reasons why our food production process is changing.[5] IoT is growing in popularity and operates in real time.[6,7] By planning, gathering, identifying, and applying big data and artificial intelligence to manage systems for services, IoT technology is developing.[8-10] Conventional farming techniques often rely on manual observation and experience-based decision making, which can result in inconsistent crop yields and resource wastage. Farmers lack timely, data driven insights into soil moisture, nutrient levels, and pest risks. There is a pressing need for an automated system that can

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collect, process, and analyze agricultural data to support intelligent decision-making. To improve agricultural productivity, machine learning (ML) techniques are used to analyze such data.[11] By transforming unprocessed agricultural data into useful knowledge, machine learning (ML) in smart agriculture increases productivity, lowers expenses, and guarantees sustainability. It is a major facilitator of contemporary precision farming since it facilitates automation, resource optimization, and predictive analytics.[12] Additionally, combining machine learning and data analysis methods expands crop prediction's potential.[13] Large datasets are processed effectively by these algorithms, which also adjust to changing circumstances to continuously increase forecast accuracy. In this regard, machine learning becomes an effective instrument for combining multi-dimensional data sources, including weather information, satellite imagery, and assessments of soil condition.[14] The confluence of IoT-enabling algorithms for learning in agriculture represents an evolutionary step toward precision farming, enabling immediate tracking, accurate forecasting, and sustainable resource usage.[15] This study focuses on the development of a prototype smart agriculture system designed for small- to medium-sized farms. The IoT network is limited to sensors measuring temperature, humidity, and soil moisture. Machine learning models are trained using sample datasets and tested under controlled conditions.[16,17]

1.1 Importance of agriculture in global economy and food security

In many growing and developing nations, agriculture is a vital industry that frequently accounts for 15–30% of GDP. In addition to providing livelihoods and trade, agriculture is the cornerstone of worldwide food security, ensuring that there will always be an adequate supply of wholesome food available to present and future generations.[18] Agriculture is one of the main drivers of economic stability and growth, employing over 65% of the working population worldwide, according to the World Bank. While it supports sectors like food processing, textiles, and trade in developed countries, agriculture continues to be a major source of revenue and a crucial sector for reducing poverty in developing countries.[19]

1.2 Role of IoT in precision farming and productivity improvement

Increasing crop yield and creating an intelligent cropping system are the goals of precision farming. Precision farming is the intelligent use of agricultural resources and information using communication and sensing technologies to maximize financial return and production.[20] Wireless sensor networks and precision farming transform the agricultural industry into a technological path for increasing agricultural output with the least amount of human labor. The utilization of sensor networks that are wireless in precision agriculture will provide farmers with a multitude of information, such as energy harvesting techniques, wireless communication technologies, and the hierarchy of energy efficiency.[21] AIML enables precision farming by enabling farmers to make information-driven choices to reduce waste through real-time weather, crop, and soil monitoring. information about soil, weather, and crops.[22] Recent developments in systems for irrigation have introduced agricultural irrigation instruments, motion manipulation, satellite devices, imaging technologies, and wireless connections, which track both environmental and soil conditions and assess irrigation parameters, like flow and pressure, to improve farm water utilization efficiency.[23]

1.3 Need for ML to analyse sensor data and predict outcomes

Machine learning, which may be applied in agriculture to aid in identification of diseases, crop monitoring, and decision-making, is a key component of intelligent farming.[24] These smart devices intelligently move the collected data to designated storage places.[25,26] A controller can understand the electrical signals that these sensors convert from physical

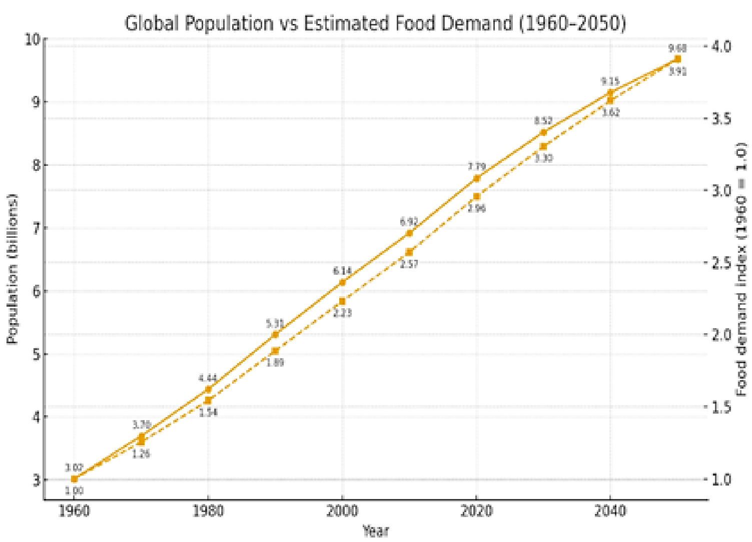

Fig. 1: Global challenges in agriculture (Population Vs Food Demand).

quantities with the help of machine learning.[27] To bridge the gap, sensor-driven agriculture needs machine learning (ML) to transform raw data into information that can be put to use. In agricultural data, machine learning finds hidden patterns, correlations, and anomalies.[28] Consequently, combining machine learning with sensor-driven agriculture turns unprocessed data into useful insights that allow for reliable forecasting that raises revenues, lowers expenditures, and supports sustainable farming methods.[29]

1.4 Research gaps in existing smart agriculture systems

Effective integration and evaluation of agricultural data produced by various Internet of Things devices, satellites, drones, and weather stations is difficult due to their lack of standardization. Even though machine learning algorithms are used to schedule irrigation, detect illnesses, and predict production, their performance can occasionally be reduced by noisy, imbalanced, or incomplete records.[30] The scalability of smart agricultural systems in large, diverse, and resource-constrained farming contexts is rarely demonstrated, despite the fact that many of them are tested on prototype or small-scale companies.[31] The spread of connected farming tools increases the risk of cyberattacks and the inappropriate use of private agricultural data, an understudied problem.[32] In order to create smart farming methods that are more effective, scalable, and able to guarantee a reliable food supply in the face of changing environmental and socioeconomic challenges, it is crucial to identify and close such research gaps.[33] The picture below illustrates the problems and advancements in global food security by highlighting the relationship between the world's growing population, rising food supplies and crop prices, and the main crops that contribute to global food energy.[34]

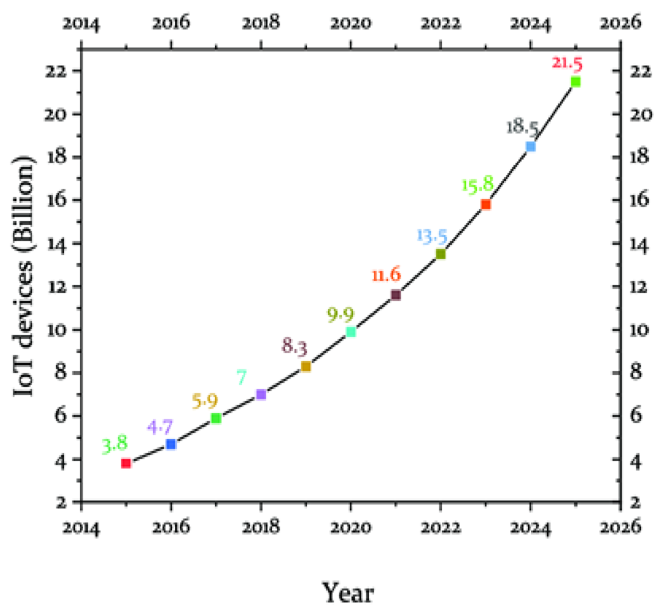

Fig. 2: Growth of IoT applications in agriculture (2015–2025).

2. Literature review

Managing spatial, temporal, and environmental factors to enhance output and raise an agriculturist's production and profitability is the focus of smart agriculture.[1] Every environmental factor varies from one place to another, including soil properties, weather, water availability, fertilizers, humidity, and temperature.[2] Due to the losses they have incurred, farmers face significant obstacles when considering quitting farming. In order to generate greater outputs, smart farming efficiently and effectively employs fewer inputs.[3] The two main trends are IoT sensors and machine-learning methods.[4] Numerous studies emphasize how crucially the massive amount of data collected by IoT devices must be handled and processed using analytics for big data and cloud computing. These technologies enable real-time decision-making and predictive analytics for proactive agriculture.[5] Automation and Robotics: Using Internet of Things-driven robots for tasks like pest management, weeding, and spraying is another well-liked tactic.[6] Drone Use: Some studies investigate the use of drones and the Network of Things to optimize irrigation, monitor agricultural health, and conduct surveillance.[7]

2.1 Databases used

The division of agriculture during exams determines the aspects that impact data gathering in the sector of agriculture. Crop productivity in hunting and crop farming is impacted by a number of factors.[8] Such a model aids in understanding how crucial it is for crops to receive adequate water. Depending on their stage of growth, different crops require varied amounts of water. Monitoring rainfall aids in scheduling crop watering. Every crop grows optimally in a certain range of temperatures.[9] When selecting crops and determining when to plant them, it's critical to understand how temperatures vary throughout the day. Crop growth can also be impacted by humidity, particularly in relation to diseases.[10] Farmers can tell when & just how much water supply is needed by using soil moisture monitors. The soil requirements of various crops vary. IoT based systems, sensor networks, machine learning applications, hardware and software integration, literature reviews, citation analysis, and pinpointing research trends are all common applications in smart agriculture. Plant biology, crop disease detection, agricultural biotechnology, and machine learning for plant health are also included in this.[11]

2.2 Keywords

IoT Agriculture: In agriculture, networked technologies such as monitoring devices, autonomous aircraft, and intelligent systems of irrigation are used to collect real-time data on crops, soil, and environmental factors.[12] Smart Farming: This refers to the incorporation of cutting-edge technologies into conventional farming methods, including robotics, drones, AI, machine learning, and the Internet of Things.[13] It emphasizes automation, sustainability, resource optimization, and precision agriculture. Farmers can more effectively monitor, forecast, and manage farming operations

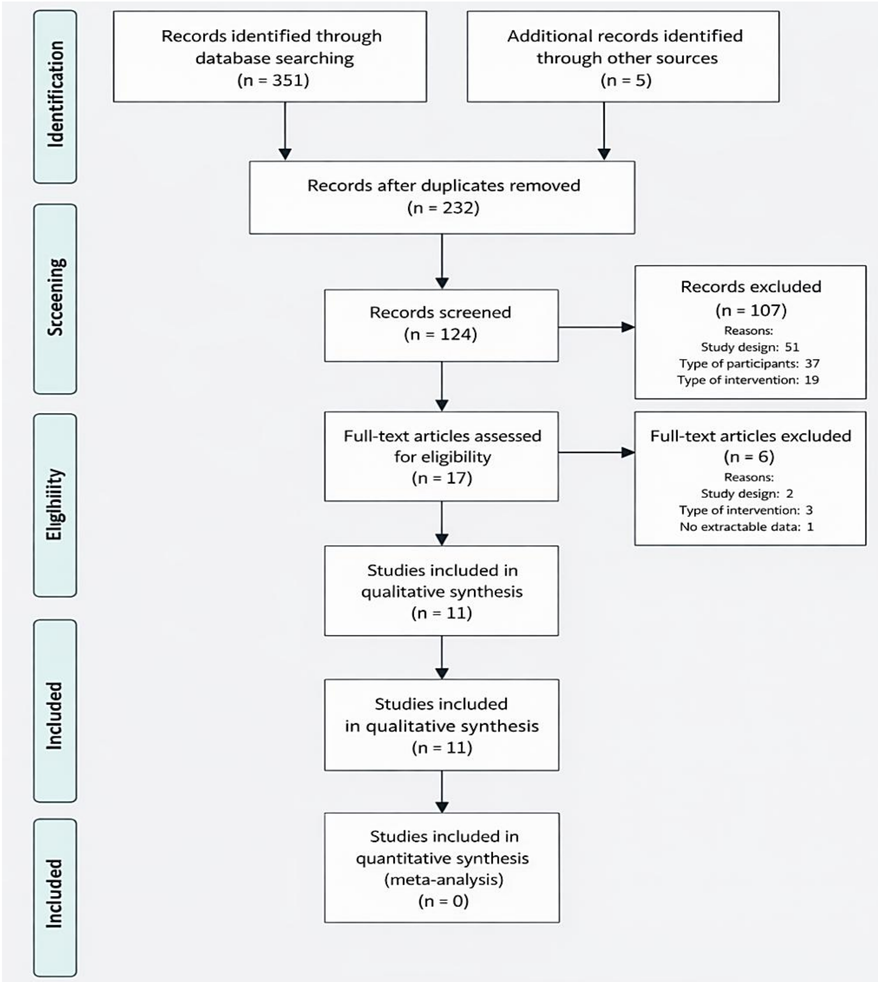

Fig. 3: Literature selection flowchart (PRISMA-style).[10]

Table 1: Summary of reviewed papers.

Title	Year	Application	Method	Key Finding
Machine Learning for Smart Irrigation	2022	Optimized irrigation scheduling	ML models (Random Forest, Neural Networks)	predicted irrigation needs reduced water usage by 25% without affecting yield.
Smart Agriculture Using IoT and ML	2021	Crop monitoring and yield prediction	IoT sensors + Machine Learning models (SVM, RF)	Real-time monitoring improves yield prediction accuracy; reduced resource wastage.
IoT-based Precision Farming System	2020	Soil moisture and temperature monitoring	IoT sensors + Data Analytics	Automated irrigation based on sensor data increased water efficiency by 30%.
Deep Learning for Plant Disease Detection	2019	Disease identification	Convolutional Neural Networks (CNN)	CNN models achieved 95% accuracy in detecting common crop diseases from leaf images.

thanks to smart farming.[14] ML in Agriculture: Large amounts of agricultural data gathered by sensors, satellites, and drones are analyzed using machine learning algorithms.[15] Crop production, disease outbreaks, soil health, and irrigation requirements can all be predicted using ML models.[16] In order to transform unprocessed data into insights that farmers can use, algorithms like Random Forests, Support Vector Machines (SVM), and Deep Learning are essential.[17] Crop Prediction: Using information gathered from IoT devices, satellite imaging, weather data, and historical agricultural records, crop prediction forecasts yield and growth patterns.[18] Accurate yield estimations can be produced by fusing IoT and ML, which aids in market forecasts, sustainable agricultural methods, and food security planning.[19]

3. IoT-based smart agricultural systems

IoT-based smart agricultural systems enable the integration of computers with a wide range of internet-connected devices. Things such as sensors, transducers, actuators, utilities, and other network-enabled devices, can now be linked through the Internet of Things (IoT) paradigm.[20] Web services function as a programming layer protocol that allows end users to interact with management, operations, functionalities, and communication interfaces. A design that promotes interoperability ensures seamless communication and integration across different components, devices, and platforms, thereby enhancing the efficiency and reliability of smart agriculture systems.[21]

3.1 Sensors

The sensors form the foundation of the system. They are positioned across the agricultural field to capture crop-related and environmental data in real time.[22] Gateway: The gateway serves as a link between the sensors and the cloud. It collects data from several sensors, analyzes it if needed, and then securely transmits it to the cloud. Communications technologies include cellular networks, Wi-Fi, Zigbee, and LoRa.[23] It carries out tasks including combining data from several sensors and cutting down on unnecessary transfers to conserve bandwidth and electricity.[24] Cloud: Utilizing cutting-edge computing techniques, the cloud serves as the primary location for storing, processing, and analysing the gathered data.[25] carries out tasks like safely storing vast amounts of farm data. incorporating outside data, including weather predictions.[26] Farmer Interface: The end-user layer that provides farmers with accessible access to the data being processed is known as the farmer interface.[27] carries out tasks such giving individualized advice on irrigation, applying nutrients, and pest control, as well as supplying real-time assessment of soil, crop, as well as weather conditions.[28]

3.2 Layers

Devices, Sensors and Microcontroller: Layer 1 is made up of devices, sensors, and microcontrollers; Layer 1 is always where the architecture starts.[29] This layer includes smart gadgets like digital glasses, electronic watches, various actuators, sensors, and smartphones, as well as industrial robots, PLCs, advanced robotics, and other microcontrollers. The relationship between people and robots is enhanced by these devices.[30]

Network, Communication, Protocols: The raw data gathered from the preceding layer is transformed into actionable information by this layer. This layer is more powerful than its predecessor because it is where foundation stations or gateways are developed.[31] Sending protocol-based notifications to production equipment is one example from the real world. Even developers can add more scientific capabilities with tools, for example, AWS Lambda function calls.[32]

Cloud Infrastructure: Using a variety of data analysis techniques, the information gathered from multiple sources is arranged in this layer based on requirements.[33] Because the acquired data is stored as needed, the information that has been processed is original. Cloud services concentrate on a single location where customers can apply analysis to data that has already been prepared. End users can save both organized and unstructured data at any time with these services. Connected data and connected services are examples of region-based data resources. These techniques facilitate the reuse of web- or cloud-based data and services.[34]

Big Data Analysis: There is a possibility of producing a lot of data when linked to the Internet of Things, which needs to be analyzed in many ways. Big data may require modifications to new optimizers or algorithms.[35] Connecting everything on Earth to the internet may seem

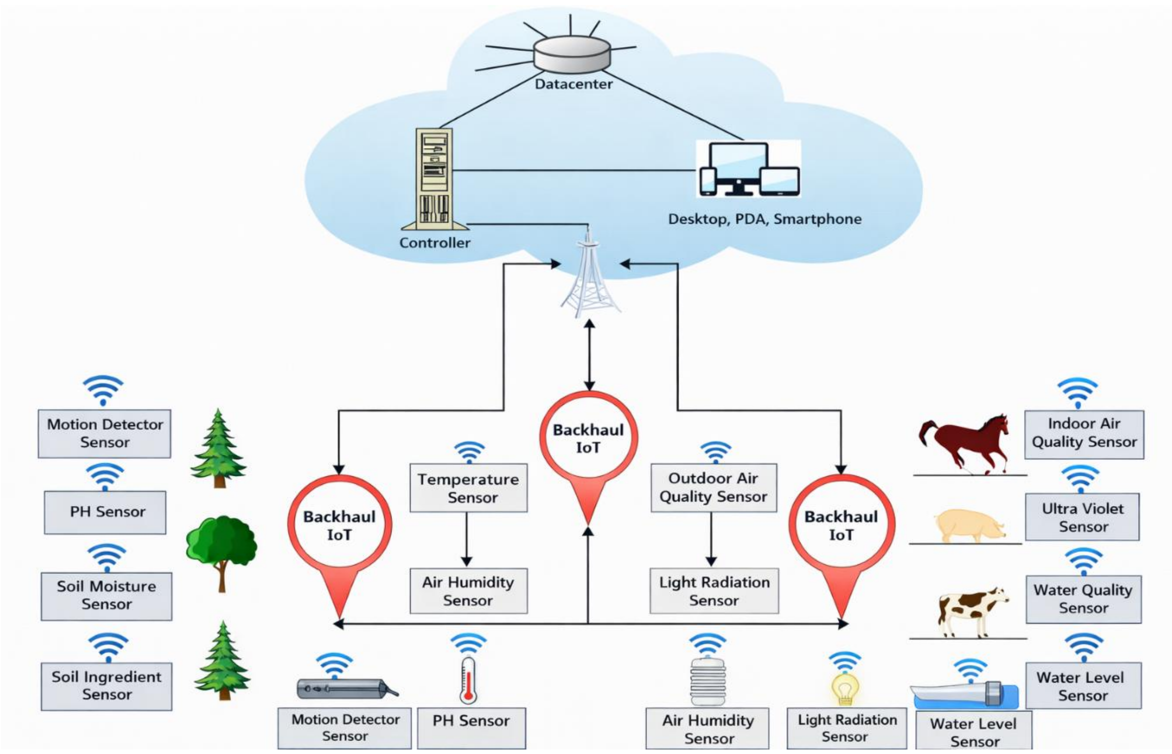

Fig. 4: IoT architecture for smart farming.

Table 2: IoT devices in agriculture.

IoT Device	Parameter Measured	Connectivity	Application
Soil Moisture Sensor	Soil water content	LoRa, Zigbee, Wi-Fi	Smart irrigation and water resource management
Temperature & Humidity Sensor (DHT11/DHT22)	Air temperature and relative humidity	Wi-Fi, Zigbee, Bluetooth	Monitoring micro-climate for crop growth
pH Sensor	Soil pH levels	Wi-Fi, LoRa	Soil quality assessment and fertilizer planning
NPK Sensor	Nitrogen, Phosphorus, Potassium content	Wi-Fi, GSM	Precision fertilization and soil nutrient balance

odd, but online services and the Internet of Things will transform our lives in the future by enabling the impossibly conceivable.[36]

3.3 Examples of IoT platforms for agriculture.

Thing Speak: This well-known free-software Internet of Things application platform is used for agricultural prototyping and research.[37] Kaa IoT Platform: Kaa is an independently developed, highly flexible Internet of Things platform. advantageous for livestock monitoring using smart irrigation and precision farming, when several sensor nodes require centralized control.[38] IBM Watson IoT: This commercial cloud-based solution integrates artificial intelligence and advanced analytics. use meteorological and sensor data to anticipate production, optimize fertilizer use, and predict agricultural diseases.[39] Microsoft Azure IoT Suite: Microsoft Azure IoT offers comprehensive IoT solutions that incorporate big data analytics and cloud integration, providing farmers with real-time decision help while keeping an eye on climate, soil health, and agricultural equipment.[40] Google Cloud IoT Core: With its sophisticated machine learning capability, Google Cloud IoT Core is built to manage extensive IoT deployments. predictive irrigation systems, satellite data integration, and extensive agricultural monitoring.[41]

4. Machine learning methods

By facilitating data-driven decision-making, machine learning (ML) techniques are essential to converting traditional farming into smart agriculture.[1] Large volumes of agricultural data, including crop photos, weather, soil parameters, and sensor readings, are gathered in real time through the integration of IoT devices.[2] Machine learning models examine this data to find trends, forecast results, and give farmers useful information.[3] The following ML techniques are frequently applied in agriculture:

4.1 ML methods

Decision Tree: A decision tree is a supervised learning technique used for classification and regression. It separates this information into branches based on feature values to produce a model that resembles a decision tree. In smart agriculture, crop types are forecasted based on information from IoT sensors about temperature, humidity, and soil properties.[4] Analyzing data from optical sensors and the surroundings to detect plant diseases or pests. providing farmers with simple-to understand instructions for making choice. It is very easy to understand and display, and it performs well with both numbers and categories of information.[5] Random Forest: Random Forest is an ensemble learning approach that builds many decision trees and combines their findings (majority vote for classification, average for regression) in order to improve accuracy.[6] Smart agriculture is employed for utilizing multi-sensor data (soil, weather, and irrigation) to forecast agricultural yield. utilizing IoT-enabled image sensors to classify plant health. effectively managing big agricultural datasets with several features.[7] It has a high accuracy and resilience to overfitting, and it can handle big datasets and missing values efficiently.[8] Support Vector Machine: SVM is a supervised learning method for regression and classification. It finds the optimal hyperplane between measurements of different classes with the biggest margin.[9] Precision farming optimizes fertilization and irrigation schedules, IoT sensors detect anomalies in soil or water quality, and smart farmland uses sensor or image data to categorize crops or predict plant illnesses. It is effective in high-dimensional domains and does effectively with small to medium-sized datasets.[10] k-Nearest Neighbors (k-NN): The simple instance-based learning method known as k-NN classifies a sample based on most of the class of the closest k u in the feature space. Using data from adjacent field sensors, smart agriculture can anticipate crop suitability or soil fertility, diagnose plant illnesses or pest infestations by comparing them to known cases, and monitor environmental conditions to inform local farm management.[11] Logistic Regression: One statistical technique for binary or multi-class categorization is logistic regression. It uses a logistic (sigmoid) function to assess the likelihood of a result.[12] Smart agriculture is used to classify crop adaptability in various climatic zones, forecast irrigation demands (yes/no) in precision farming, and estimate the likelihood of crop disease development based on IoT sensor inputs (temperature, humidity, and soil moisture).[13]

4.2 Deep learning (DL) methods

One statistical technique for binary or multi-class categorization is logistic regression. It uses a logistic (sigmoid) function to assess the likelihood of a result.[14] Smart agriculture is used to classify crop adaptability in various climatic zones, forecast irrigation demands (yes/no) in precision farming, and estimate the likelihood of crop disease development based on IoT sensor inputs (temperature, humidity, and soil moisture).[15]

4.2.1 Convolutional Neural Network (CNN)

CNNs constitute specialized neural networks that are made to recognize patterns and images. They employ fully linked layers for classification and convolutional layers in order to automatically learn features of space like as edges, textures, and forms.[16] From low-level features (edges) to high-level features (plant disease patterns), CNNs automatically learn hierarchical representations are employed in smart agriculture to detect agricultural diseases. IoT cameras or drones take pictures of leaves and fruit, and CNNs determine if the crop seems healthy or sick.[17] Additionally utilized for the analysis of soil and leaf images, fruit grading and harvesting, and weed identification.[18]

4.2.2 Long Short-Term Memory (LSTM)

Recurrent neural networks (RNNs) of the LSTM type are made to handle sequential and time-varying information. Memory cells and gates (which include input, forget, and return gates) that regulate what data is kept, updated, or forgotten are used by LSTMs to address the vanishing gradient problem, in contrast to conventional RNNs.[19] They are therefore quite good at identifying long-term dependencies. Weather forecasting, yield for crop prediction, irrigation management, and disease spread forecasting are all done with LSTM in smart agriculture.[20] LSTMs can model continuous time-series data from IoT sensors as well as weather stations, such as temperature, humidity, and rainfall, to predict future trends. Long-term temporal dependencies are effectively handled by LSTM.[21] Large datasets are necessary for high accuracy.[22]

4.2.3 Autoencoders

Unsupervised neural networks called autoencoders are designed to acquire effective data representations. In order to reconstruct the original input with this constrained form, the encoder compresses the input information to generate a latent representation, and the decoder does the same. There is an anomaly if the replication error is significant. Because of this, autoencoders are helpful for dimensionality reduction and anomaly detection.[23] The autoencoder is utilized in smart agriculture to identify faults in IoT sensors by identifying anomalous signals from sensors measuring temperature, nutrient levels, or soil moisture. Additionally, in Early Warning Systems, Data Denoising, and Crop Anomaly Detection.[24]

4.2.4 Hybrid CNN + LSTM

This hybrid model combines the temporal sequence learning of LSTM with the spatial feature extraction of CNN. First, spatial patterns are extracted by CNN.[25] In order to capture temporal dependencies, LSTM then processes the above characteristics over time.[26] such as sensor grids or image characteristics. The hybrid The CNN network + LSTM is utilized in Smart Agriculture to monitor crop diseases over time. CNN recognizes disease characteristics from photos, while LSTM monitors the illness's progression over a period of weeks or months.[27] LSTM forecasts future water demand, whereas CNN evaluates soil pictures for texture and quality.[28] While LSTM predicts yield by modelling seasonal patterns, CNN analyses drone photos of fields.[29] Integrating temporal (time-series) and spatial (image) data is the aim of Hybrid CNN + LSTM. Additionally, for multimodal agricultural datasets, it is considerably more precise than CNN or LSTM alone.[30]

5. Agriculture sensors and devices

Sensors are crucial to agricultural IoT systems because they gather data. The data that these smart gadgets gather is sent to designated storage locations. The temperature sensor is one of the most crucial kinds of sensors utilized in agriculture.[31]

5.1 Sensors

Temperature Sensors: These devices track the temperature of the air and soil. These are essential components of farming systems based on IoT.[32] pH Sensors: A sensor that detects pH can be used to determine whether the soil has excessive nitrogen or not enough nutrients. The pH of the soil is measured by the second kind of sensor. Plants may grow sickly, little leaves with brown patches if the soil is either alkaline or too acidic.[33] Soil Moisture Sensors: By determining how much water plants require, these sensors can enhance irrigation. There are two varieties of soil moisture sensors: touching and non-contact.[34] Humidity sensors: Plant leaves function best when they are not overly wet, so it's critical to know the humidity level. Farmers can determine when what and how ample water they ought to use by monitoring humidity.[35] Weather sensors include a) a rainfall sensor, which uses a rain gauge to detect the amount of rain that falls, including the amount that falls in an hour. It indicates the amount of rain that is falling right now.[36] b) Wind Speed Tracker: A wind speed sensor indicates the direction of the wind. The location affects its accuracy.[37]

5.2 Evaluation of IoT and drone-based systems: pros, cons, accuracy, and energy challenges

Nutrient and Cameras (Drones): These devices measure phosphorus, potassium, and nitrogen (NPK), which is useful for determining when to harvest, enhancing security, and assessing crop health. Blue, red, and green RGB camera sensors are able to record visual information that is then analysed by intelligent algorithms.[38] Farmers may determine the type and amount of fertilizer to use by measuring the

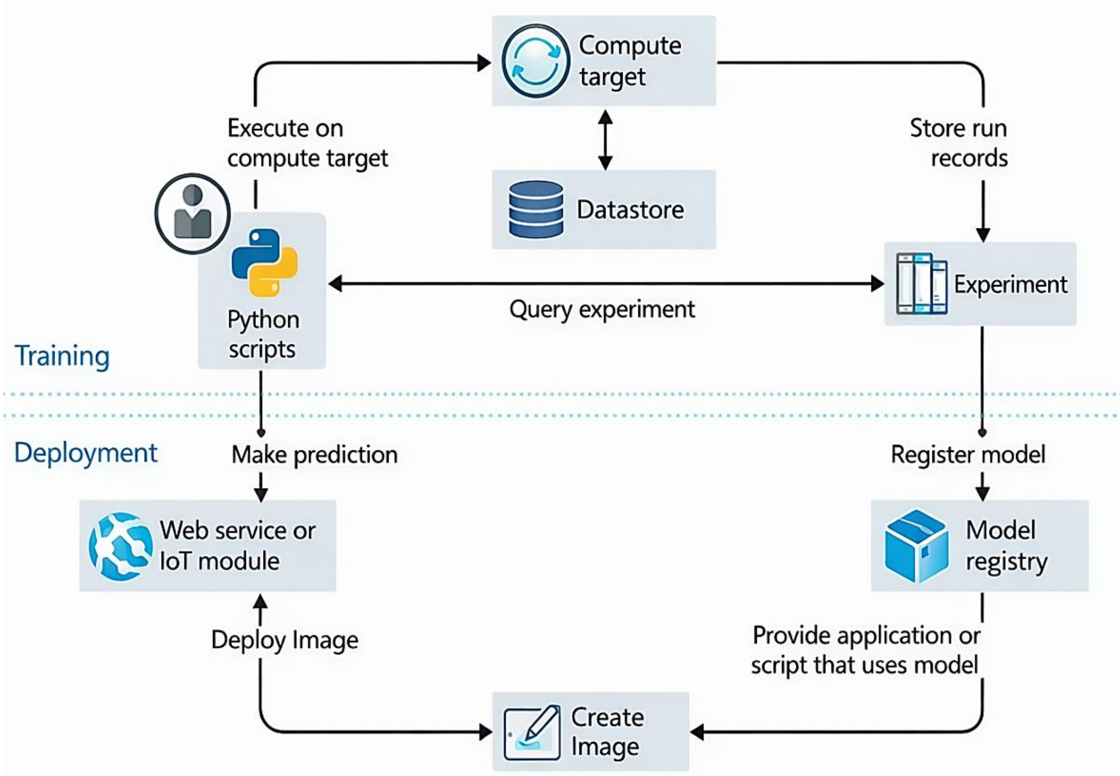

Fig. 5: Workflow: sensor data → ML model → prediction → farmer alert.

Table 3: Comparison of ML/DL models in agriculture.

Model	Input Features	Dataset Used	Accuracy (%)	Pros	Cons
Support Vector Machine (SVM)	Leaf images, soil properties, weather data	Plant Village, UCI datasets	85–92	Works well with small datasets, good for classification	Struggles with large datasets, tuning is complex
Random Forest (RF)	Soil nutrients, temperature, rainfall, crop yield records	Kaggle crop yield dataset, regional agricultural data	88–94	Handles noisy data, less overfitting	Less interpretable, slower with very large data
k-Nearest Neighbours (k-NN)	Crop disease images, sensor data	Plant Village, field survey data	80–87	Simple, effective for small datasets	Computationally expensive, sensitive to noise
Artificial Neural Network (ANN)	Weather, soil moisture, yield history	Custom farm datasets, FAO data	90–95	Learns complex relationships, adaptable	Requires large datasets, “black-box” nature
Convolutional Neural Network (CNN)	Crop/leaf images for disease detection	Plan Village (50k images)	95–99	High accuracy in image recognition, automates feature extraction	Needs large label datasets, high computational power

NPK levels, which indicate how nutrient-rich their soil is. Energy concerns, accuracy, and pros and disadvantages. Benefits of smart agriculture: There is a noticeable loss in parameters when a fully connected layer is used in place of the convolution layer.[39] By optimizing the margin amongst categories through the use of kernel functions, it makes effective data grouping possible.[40] Intelligent pest management, fertilization, and irrigation cut waste and boost productivity. Predictive analytics (using ML) and real-time monitoring (using sensors) aid in resource optimization and agricultural output growth.[41] Drawbacks: Scaling large datasets is often difficult. Having overfits with too many characteristics, making it difficult to comprehend the complex relationship between features.[42] Occasionally, results from inaccurate data sets may contradict one another To use and comprehend smart technology, farmers or employees could require training IoT systems need frequent maintenance and are susceptible to failure in severe settings (dust, rain, *etc*.[43] Traditional agricultural expertise and resilience in the event of a system collapse may be diminished by reliance on technology.[44]

5.3 Energy issue

Data Preprocessing: Exploratory Data Analysis (EDA), was used using Jupyter Notebook modules like Pandas and NumPy to automate this information cleaning procedure.

Model Training: Characteristics like temperature, humidity, rainfall, soil pH, and NPK levels are all included in the training dataset.[45]

Model evaluation: The many evaluation criteria used to gauge the effectiveness of the models in use are presented in this section. It is a crucial stage in the creation of models and is frequently used to show how reliable a model is in terms of performance.[46]

Data Source: A sampling of soil and historical climatic data from farms along the Wannune axis served as the study's data sources. Among the factors are soil pH, humidity, rainfall, phosphorus (P), magnesium (K), and nitrogen (N).[47] Data collection: Temperature, humidity, light levels, moisture in the ground, and other pertinent factors are among the many variables that the sensors are responsible for gathering data on.[48]

6. Role of IoT in agricultural management

6.1 Crop monitoring

IoT aids in monitoring the soil's concentrations of vitamins, potassium, phosphorus, nitrogen, and other minerals. Farmers may use this to determine when and how much fertilizer to apply.[49] This ensures that crops get the nutrients they need to grow healthily and produce high-quality food without requiring too much or too little fertilizer. It also reduces trash and helps the environment. IoT also keeps track on climatic factors like temperature, light, and moisture to give farmers constant updates on their crops.[50]

6.2 Irrigation management

Smart irrigation uses Internet of Things (IoT) sensors to track soil moisture, weather, and other variables. Weather

Table 4: Agricultural sensors.

Application	Method	Features and Benefits
Precision farming resource waste	IoT sensors track plant-level data; ML gives targeted input (fertilizer, pesticide)	Boosts yield, reduce
Yield Prediction	IoT stations collect real-time local weather data; ML improves forecast accuracy	helps in planning
Weather Forecasting	IoT wearables track animal health; ML detects illness or stress patterns.	better planning for planting
Livestock Monitoring	IoT cameras scan fields; ML identifies and locates weeds reduces herbicide use	Improves animal health
Weed Detection	IoT tracks harvest, storage, and transport; ML predicts demand and spoilage risk	enables targeted weeding

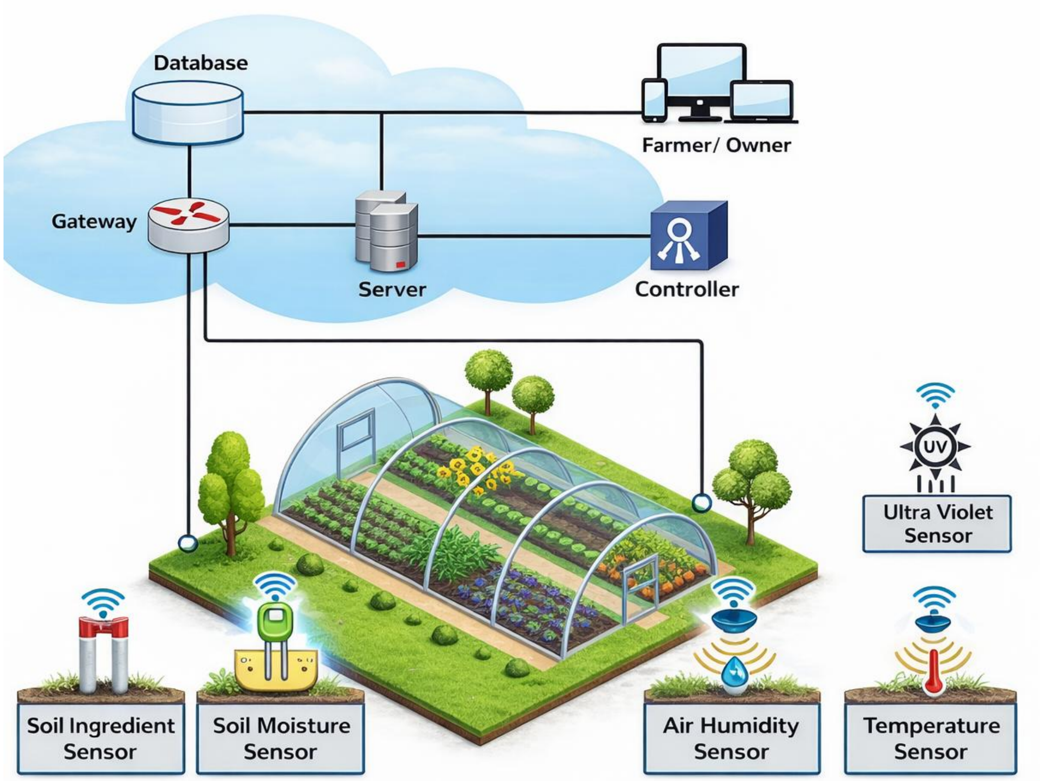

Fig. 6: Application of IOT and machine learning in agriculture with sensor placement in crop fields monitoring.

conditions, water in the soil, and even sunshine are all measured by these sensors. The data is wirelessly received by a central system, often situated in the cloud.[51]

6.3 Precision livestock farming

Crop management in farming involves the use of drones, Internet of Things sensors, and data analysis. photos of plantings are taken by drones fitted using specialized cameras and sensors. These photos are then processed by advanced algorithms to detect problems like pests or diseased crops. By helping farmers make well-informed decisions, this lowers costs and boosts agricultural production.[52]

6.4 Supply chain and storage monitoring

Real-time data is transmitted to a central network from connected gadgets in packaging and storage locations.[53] This provides all parties with comprehensive information on the location and state of the items. IoT, for instance, maintains fruits and vegetables at the proper humidity and temperature while they are being transported. Additionally, it offers real time tracking, which improves the efficiency of the supply chain by assisting in the movement of commodities from fields to factories and ultimately to consumers.[54]

7. Challenges and limitations

7.1 Technical

Connectivity is one of the major challenges in implementing IoT in agriculture, as reliable system performance depends on stable internet access, particularly in remote rural areas where network infrastructure is often weak.[55] This makes it hard to send data and check on things in real time.[56] To fix this, building better internet infrastructure in those areas can help create a system that reliably sends and receives data.[57] Security and privacy of data: Data security becomes increasingly crucial as more is gathered. Data that has been compromised may be taken, altered, or distributed without authorization. Farmers may suffer financial losses, reputational harm, and even legal problems as a result of this.[58] To prevent this, the risk can be decreased by implementing measures such data encryption, establishing stringent access controls, and maintaining security.[59]

Table 5: Applications of IoT and ML in agriculture.

Challenges	Solutions
Unpredictable weather	ML models and IoT weather stations → better, more accurate local weather forecasts
Water scarcity	Smart irrigation systems → IoT soil sensors and ML determine exactly how much water crops need
Crop diseases and pests	Drones with image recognition → ML detects signs of disease or pests early from data collected by IoT devices
Overuse of fertilizers and pesticides	Precision farming → IoT monitors soil and crop conditions; ML suggests the best amounts to use
Low yield or productivity	Yield prediction → ML analyses past data and sensor info to help with planting and harvesting.

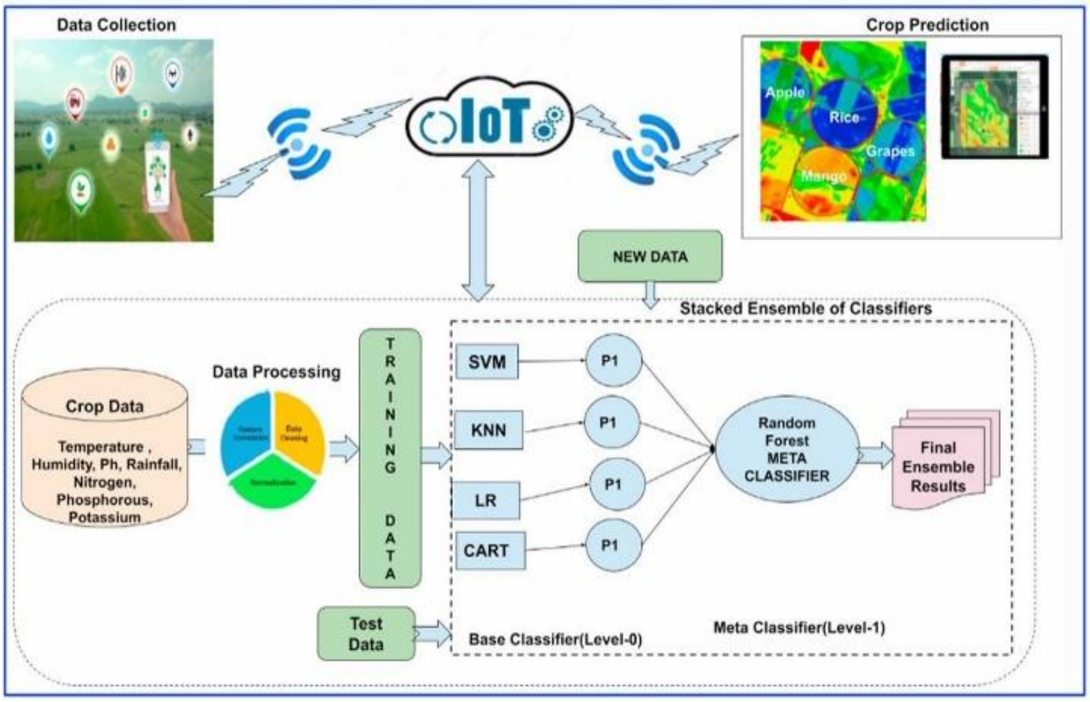

Fig. 7: Smart agriculture workflow (farm sensors → cloud/ML → farmer mobile app).

Interoperability and standardization: It can be hard to make sure different IoT devices and systems from different companies work together without problems. For this to work, the industry needs to agree on common standards and work together.[60]

Scalability: By automating processes that would normally need human labour, IoT in agribusiness helps decrease waste, minimize environmental impact, and save time and money.[61]

7.2 Environmental

Adoption and awareness: Getting farmers to use IoT can be tough. Some are hesitant to invest in new tech because they don't understand the benefits, don't trust the technology, or don't have enough information to decide. So, creating programs that teach farmers about the benefits of IoT and help them overcome their doubts is important.[62] Smart Grids, Microgrids, and Renewable Energy: Due of sensors, navigational systems, and data transport, smart farming requires a lot of electricity. Using alternative sources of energy helps address persistent power problems in rural places. Local energy systems include microgrids and smart grids. Additionally, new energy storage systems may store heat and power, increasing the efficiency of energy consumption.[63] Environmental and Sustainability Concerns: IoT devices that run on batteries need to be replaced or charged often, which costs money and creates a lot of electronic waste. Solar-powered IoT devices are being developed to help, but they are still expensive and don't work well in areas with little sunlight. Also, broken or faulty sensors need to be replaced, which adds to costs and e-waste. Making IoT devices more durable, weather resistant, and recyclable is important to reduce their environmental impact.[64] Technology Accessibility: Using cutting-edge technology might be challenging in some areas due to a lack of new tools and reliable internet. Farmers find it challenging to employ intelligent agricultural practices as a result.[65] For these techniques to gather and exchange sensor data, high quality equipment and a fast internet connection are required. Farmers in areas without these find it more difficult to take advantage of these advancements as they are unable to properly utilize the newest farming equipment.[66] Regulatory Compliance: Farmers using precision farming have to follow many rules set by national and municipal governments regarding environmental protection, land management, and data use. These rules can make things more complex and expensive.[67] Sticking to all the rules about data, how land is used, and how the environment is treated can be a big challenge, adding more time and cost for farmers using precision farming. It helps maintain transparency by recording farming practices, fertilizer use, and pesticide applications in line with regulations. Compliance also builds trust among consumers and policymakers, supporting sustainable and legal agricultural practice.[68]

7.3 Social/economic

Farmers may benefit from using Technology in farming by producing higher-quality, more transparent, and sustainable goods.[69] This makes companies stand out from the competition, satisfies consumer demand for environmentally friendly items, and raises the price at which they sell their goods. Adopting IoT gives farmers a significant opportunity to increase revenue and set their goods apart in a competitive market, as consumers' concerns about environmentalism and transparency grow.[70,71] IoT helps farmers save money by managing resources better and using predictive maintenance.[72] With real-time data, they can run their farms more efficiently, cut down on waste, and boost their profits over time.[73]

8. Emerging technologies in smart agriculture

8.1 Edge AI and federated learning for local farm data analysis

Drones are increasingly being used in farming as IoT and connectivity technologies advance.[74] Drone abilities in agriculture could be greatly improved in the future by AI. AI may be used by drones to help with tasks including agricultural inspection, water management, crop health monitoring, planting, crop spraying, and soil analysis.[75] Tracking agricultural conditions is made easier by drones fitted with a variety of sensors, including ordinary cameras, thermal photos, 3D images, and multispectral photography. Disease detection, plant density measurement, and soil health monitoring.[76]

8.2 5G/6G for real-time farm monitoring

In order to influence the direction of agriculture in the future, it is crucial to encourage global collaboration and the open exchange of data in the area of precision farming.[77] The goal of this cooperative is to create a comprehensive yet accurate knowledge database that will provide agricultural decision-makers with a wealth of helpful information.[5] Through international collaboration, farmers may gather data from diverse regions. Combining this worldwide expertise yields a useful resource for enhancing precision farming techniques, honing forecasts, and implementing sustainable practices over a wider region. This ultimately supports the global goal of ensuring food security and promoting agriculture that is better for the environment.[78]

Table 6: Challenges vs solutions in smart agriculture.

Challenges	Solutions
Unpredictable weather	ML models and IoT weather stations → better, more accurate local weather forecasts
Water scarcity	Smart irrigation systems → IoT soil sensors and ML determine exactly how much water crops need
Crop diseases and pests	Drones with image recognition → ML detects signs of disease or pests early from data collected by IoT devices

8.3 AI enabled drones for precision spraying

Drones are increasingly being used in farming as IoT and connectivity technologies advance. Drone abilities in agriculture could be greatly improved in the future by AI.[79] AI may be used by drones to help with tasks including agricultural inspection, water management, crop health monitoring, planting, crop spraying, and soil analysis.[80] Tracking agricultural conditions is made easier by drones fitted with a variety of sensors, including ordinary cameras, thermal photos, 3D images, and multispectral photography.[81] Disease detection, plant density measurement, and soil health monitoring.[82]

8.4 Blockchain for food supply chain traceability

Smart farming could be revolutionized by these three technologies. The sustainability, effectiveness, and transparency of farming could all be enhanced by these techniques.[83] One problem is that most contemporary artificial neural networks depend on the use of cloud services, which necessitates frequent internet connections and substantial data transfers.[84] Edge AI processes data directly on agricultural machinery, which is faster and more reliable, especially in areas with poor internet.[85] Drones and Edge AI-powered sensors can examine crop images, detect pest problems, and adjust watering schedules without the need for extra data processing. Remote farms benefit from this speedy decision-making.[86] Edge AI will be essential to automated precision farming as AI technology becomes more effective and reasonably priced.[87] A novel approach to enhancing supply chain transparency and trust is the tracking of agricultural products from start to finish using blockchain technology.[88] From the agricultural process to the consumer, blockchain documents and safeguards every phase of a product's lifecycle. This lets consumers know where their food comes from and helps verify whether products are sustainable, organic, or properly traded.[89] It quickly identifies possible contamination areas during a recall, increasing consumer confidence and helping to guarantee food safety.[90] This protects public health and benefits the entire food industry. In summary, the technology of Bitcoin is a powerful tool that helps create a future where openness is at the heart of agriculture. Accountability and trust.[91]

8.5 Multi-modal prediction

By improving resource efficiency and minimizing environmental effect, precision farming techniques may be adapted for implementation in metropolitan and vertical farming, which has several advantages.[92] Utilizing data-driven strategies in tiny areas reduces the total environmental impact, conserves water, and makes better use of available resources.[93] This strategy promotes sustainable practices while satisfying the rising demand for locally produced, fresh food. All things considered, adapting precision farming for vertical and urban agriculture is a clever strategy to satisfy consumer demand for locally grown, environmentally friendly products.[94]

9. Conclusion

Farmers may increase efficiency, production, and sustainability by employing smart irrigation, precision farming, supply chain management, smart greenhouses, animal tracking, agricultural drones, pest and disease control, and crop and soil monitoring. The review's key findings demonstrate the manner in which IoT technology is significantly altering agriculture. Accurate real-time information greatly boosts output and helps keep crops from withering. Farmers can remotely monitor and control crops in real me thanks to IoT technology. All of the crucial farming-related updates and statistics are available on the Blynk app. All farming operations are fully protected by this technology, increasing output while requiring less labour. Combining IoT with Machine Learning gives a strong chance to boost productivity, sustainability, and decision-making in farming. However, there are still big challenges, like high costs, limited internet in rural areas, and low understanding of technology among farmers. At the same time, there are great opportunities, such as precision farming, early disease detection, and climate-friendly solutions that can change how food is produced. Still, there are key research areas that need more attention—like creating affordable and scalable systems, ensuring data can be shared easily, and making tools that are easy for farmers to use. Fixing these gaps is important to make smart farming accessible, dependable, and effective around the world. These technologies offer powerful capabilities to increase production, improve resource usage, and lessen environmental damage. There are still issues, though, such as expensive setup fees, spotty internet in rural locations, and farmers' lack of technological expertise. However, there are also opportunities that are transforming farming, such as automation, early danger identification, and precision farming. Important research topics including developing solutions that function in local settings, standardizing data, and constructing cost-effective systems require additional focus in order to fully realize this promise. Building robust, effective, and equitable food systems for the future requires addressing these issues. Farm Beats is a well-known and affordable Connectivity of Things (IoT) solution for farming. It makes use of TVWS, an affordable long-range technology, to support high-speed sensors. Farm Beats' weather-sensitive, sunlight-powered wireless device base station and sophisticated gateway ensure that services are available both globally and offline. The drone's battery life is further increased by its enhanced path planning algorithms. The system is already being used by farmers for three purposes: storage monitoring, animal monitoring, and precision farming. Two farms have been used to test the technique. In order to develop more Farm Beats platform apps in the future, we are working with farmers. Technological speaking, there is a lot of promise for improving the scalability and reliability of systems with developments in power efficient detectors, Ambient AI, and cryptocurrency for secure data processing. However, there are still a lot of unanswered questions. The lack of practical testing for AI-based systems for identification in complex environments, such intercropping or agroforestry, is a major issue, especially in tropical and subtropical areas. Furthermore, the absence of open-source, vendor-neutral frameworks limits the manner by which data may be used, analysed, and shared across national borders, particularly in middle- and low-income nations. As networks with Edge AI and driverless expand, many setups continue to face ethical and cybersecurity issues such as information privacy, structure transparency, and system integration into smart farming systems. In conclusion, the complete potential of machine learning and Internet of Things (IoT) in agriculture requires interdisciplinary cooperation, ethical application, and fair access. Addressing the current issues will be essential to building robust, flexible, and sustainable food systems for centuries to come.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable

Use of artificial intelligence (AI)-assisted technology for manuscript preparation

The authors confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript and no images were manipulated using AI.

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