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A Survey on Crop Management in Smart Agriculture

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Abstract

The agricultural sector's importance is highlighted by the upcoming global population growth predicted by the food and agriculture organization. This growth will lead to increased food demand. However, traditional farming methods require a lot of time and effort and result in diminishing returns. Recent technological advancements, especially in the Internet of Things (IoT), are changing this landscape by introducing smart agriculture. Smart agriculture aims to improve decision-making and crop management using IoT's connectivity and data analysis capabilities. Artificial intelligence (AI) is becoming crucial in this context, offering speed, accuracy, and cost-effectiveness. Machine learning, a type of AI, is beneficial in detecting yields and forecasting weather. This survey highlights the evolving field of intelligent agriculture, covering topics like crop monitoring, and anomaly detection, and explains the main challenges in farming practices.

1. Introduction

The agriculture sector attracts significant attention, mainly due to the expected increase in the global population. According to the food and Agriculture Organization report, the global population is estimated to increase by 2 billion by 2050 [1]. Consequently, there is a rising demand for food. Additionally, agriculture represented approximately 58 percent of the source of income for most countries [2]. However, reliance on traditional farming methods consumes farmers' time and effort and decreases productivity.

In recent years, significant advancements in technology and communication have led to the emergence of the (IoT). It refers to how intelligent and self-adaptive objects are connected to the internet to communicate and interact with each other [3]. This innovation has several applications in various domains, such as healthcare, transportation, and the development of smart cities [4]. IoT represented an opportunity to transition from traditional farming practices to smart agriculture in the agricultural sector. By utilizing cameras and sensors, continuous monitoring of crops becomes feasible. As a result, this enables streamlining automated decision-making processes [5].

Smart agriculture can be defined as using modern information technologies to acquire, process, and analyze multi-source data characterized by high spatial and temporal resolution, all to enhance operational decision-making and crop production management, as shown in Figure 1. The main objectives are to increase productivity, soil degradation, efficient water use, and decrease the use of chemicals for cultivation. Furthermore, it improves crop quality and quantity and reduces production costs [6].

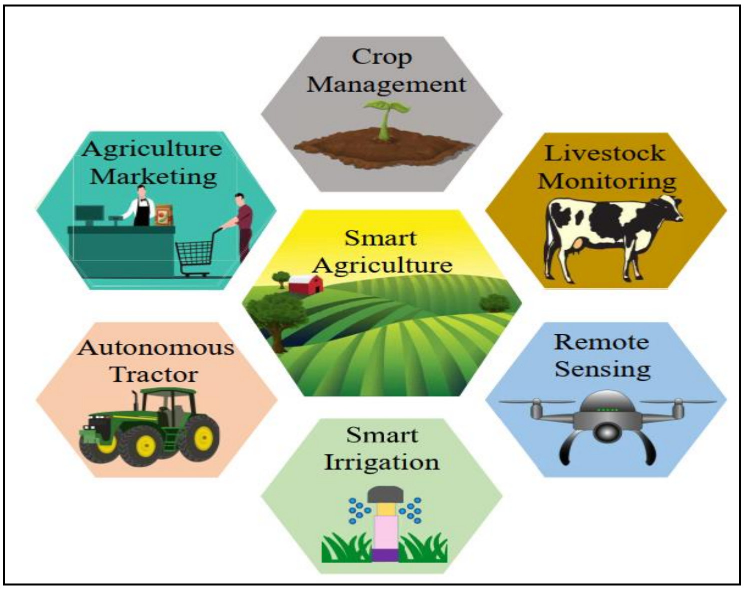

Figure 1: Smart Agriculture Overview [7].

AI is a vital software development research solution. Al in agriculture helps with speed of performance, high accuracy, flexibility, and reduced costs. AI helps farmers take advantage of their agricultural talents. In addition, it also leads to increased returns and improved quality at the lowest costs [8]. AI has emerged in three essential categories in agriculture: predictive analytics, crop and soil monitoring, and agricultural robotics. Smart agriculture combines traditional and artificial intelligence methods to improve the economy by monitoring crop growth. AI technologies, particularly machine learning algorithms, are instrumental in transforming traditional farming practices into innovative agriculture solutions [9].

Machine learning applications in smart agriculture encompass various tasks, including yield detection, disease identification, weed management, irrigation optimization, soil analysis, crop quality assessment, and weather prediction. By using the power of AI and machine learning, farmers can leverage data collected from agricultural IoT platforms to make informed decisions, optimize resource allocation, and enhance productivity [10].

Several surveys and literature reviews have been published related to smart agriculture. Talavera et al. [11] performed a systematic literature review of IoT applications in environmental and agricultural industrial fields from 2006 to 2016. The applications were divided into four groups: logistics, control, prediction, and monitoring. Moreover, Rettore et al. [12] review state-of-the-art smart agriculture security, focusing on open-field agriculture and describing its architecture and security concerns, presenting the primary challenges and future approaches. They emphasize the significance of security in building robust and effective systems and the availability and accuracy of data in future solutions to assist farmers. In addition, Fatima and Mahmood [13] conducted a systematic review and meta-analysis of semi-supervised learning models for smart agriculture. They determine a structure for various semi-supervised learning models, define the search strategy, and extract performance metrics, drawbacks, and benefits.

Idoje et al. [14] presented a review of innovative technologies in agriculture, such as AI, machine learning, cloud computing, and the IoT, as well as how they were used in smart farming.

Yang et al. [15] provided a review of research studies and current works to explore best practices for raising yield and caliber in smart agriculture. This study focused on methodologies including big data analytics, autonomous vehicle monitoring, surveillance and monitoring, and practical and precise methods for smart agriculture. In addition, researchers have identified the opportunities and challenges associated with integrating IoT devices in agriculture and suggest how these technologies can enhance food production and manage the growing human populace. It highlighted the challenges in obtaining the advantages of intelligent and connected IoT devices in agriculture, but it made no recommendations or offered any specific solutions to these challenges. Chamara et al. [16] introduced a review to create and construct Agriculture-IoT systems for crop, soil, and microclimate monitoring, the researchers reviewed a technical guide. The review determined the kinds of sensors and actuators used, primary control boards, farming practices, crops observed, communication technologies and protocols, power supply, and energy storage used in Ag-IoT systems by analyzing publications between 2011 and 2021. This study aims to replace labor-intensive, experience-based agricultural production decision-making with an automated, data-driven method by utilizing Ag-IoT technologies to access real-time field data. Due to their inflexibility in customized developments, commercial platforms are limited in Ag-IoT system development adoption. The findings' relevance to indoor farming situations may be limited by the Ag-IoT system development's emphasis on outdoor surroundings rather than interior conditions.

2. Related Works

Several studies have been published related to crop management in smart agriculture. They are divided into various application areas as shown in Table 1.

Li et al. [17] suggested a semi-supervised learning method for identifying an early-warning vegetable pest flea beetle. The model combines the unsupervised learning technique iterative self-organizing data analysis techniques algorithm (ISODATA) with labeled historical data. The algorithm extracts association rules as supervised information from labeled historical data. The accuracy of the semi-supervised learning approach is assessed using the Guangdong vegetable pest flea beetle experiment findings. Compared to RBF neural networks, support vector machines, and k-mean clustering, the semi-supervised learning approach provides a higher accuracy rate for early warning and prediction. Although the semi-supervised learning algorithm works effectively, expert knowledge of plant protection is not included in the semi-supervised learning system.

Zhang et al. [18], suggested a locally linear embedding (SLLE) approach that is semi-supervised and uses leaf images to classify plant leaves. The K-Nearest Neighbor (K-NN) Classifier is used because of its simple structure and quick training time. The algorithm performs dimension reduction to speed up the classification and comprehension of plant leaf features. The experiment's outcomes demonstrate how effectively the suggested method works with data from leaf images with a manifold structure. Combining the proposed approach with simple classifiers produces promising recognition results.

Wang et al. [19], the researchers developed a hybrid wireless sensor and actuator network (HWSAN) prototype for precise soil property measurement and precision irrigation. Wireless sensor nodes, irrigation control nodes, a gateway, a central node, and a cellular modem were all part of the HWSAN system. The system automatically sampled soil characteristics. The system collected and transmitted field data, with a data accuracy rate of more than 97% and a data packet transmission rate of 84.76%. The data included measurements of the near-surface temperature, electrical conductivity, and soil moisture at various depths. Sensor nodes could be added or removed quickly and without requiring reconfigurations because of the HWSAN system's high flexibility and robustness in the data-collecting layer. The system used a power management approach to preserve energy and prolong the battery life of the sensor nodes.

H. Lee et al. [20] utilized convolutional neural networks (CNN) to learn unsupervised feature representations for 44 plant species. To visualize the learned features and understand their significance for plant identification, it also uses deconvolution networks (DN). Utilizes leaf images to identify plants and learn their features. The MalayaKew (MK) Leaf Dataset, which includes 44 classes of plant species gathered at the Royal Botanic Gardens, Kew, England, is used for the experiments. The CNN model using the learned features achieves a 99.5% classification accuracy for the plant species. The CNN-based method performs better than traditional approaches that depend on manually created features. In comparison to the state-of-the-art method, it yields consistent and better results. Specific leaf patches are misclassified due to environmental factors like insect damage and wrinkled surfaces that influence the leaves' health.

Pérez-Ortiz et al. [21] provided a system for mapping weeds using unmanned aerial vehicle (UAV) imagery. Partitioning the image and combining crop row identification with spectral information is used to distinguish weeds from crops. The system uses classification techniques to distinguish crop, soil, and weed pixels. Various machine learning paradigms are compared to identify the best-performing approaches, including supervised, semi-supervised, and unsupervised methods. The performance of support vector Machin (SVM) and k-Nearest Neighbors (k-NN), two well-known classification techniques, is tested. According to the results, the system achieves excellent performance with very little labeled data combined with unlabeled data. This encourages the development of site-specific weed control tactics through weed maps. UAV imagery is an efficient alternative for early weed mapping since it provides ultra-high spatial resolution. The technique makes distinguishing between weeds and crops easier using crop row detection. A discussion of the potential limitations or challenges of employing UAV images for weed mapping, such as how the weather may affect the quality of the photos or the requirement for specialized equipment and knowledge to operate UAVs, would have been helpful.

F. Li et al. [22] proposed a greenhouse monitoring system based on the (IoT) to effectively control a complex, changeable greenhouse system using a fuzzy neural network. The system utilizes ZigBee protocol for mobile communication networks, alarm messaging data transmission, and wireless communication. Environmental information is collected through many greenhouse sensors, including humidity and temperature. The system is suitable for complex greenhouse control because its simple structure, flexible networks, easy expansion, and low cost characterize it. Does not address the system's scalability or adaptability to other greenhouse sizes or configurations, not offer a comparative analysis or evaluation of the suggested system versus current greenhouse monitoring systems or control strategies.

(Onal et al. [23] proposed an extended IoT framework that combines big data analytics, machine learning, and semantics to analyze weather data and detect sensor anomalies. Phases like data collection, extract-transform-load (ETL), semantic processing, and learning are all included in the framework. For weather clustering and sensor anomaly identification, the authors use the k-means clustering algorithm. The dataset contains United States of America (USA) weather data from 8000 distinct weather stations across

North America. It includes information on various meteorological parameters, including air temperature, humidity, wind speed, and pressure. The data analysis outcomes show that the suggested framework may successfully extract meaningful information from the complex weather dataset. High similarities between the clustering findings and various feature combinations indicate that the framework accurately recognizes geographical regions based on meteorological data. The suggested system has the advantages of managing large data sets, identifying sensor anomalies, and extracting hidden features. The study notes it can be more challenging to analyze results when there are missing data, such as pressure data.

Durai et al. [1] presented a proposal to include an expert system that integrates sensor networks with Artificial Intelligence systems, such as Neural Networks and Multilayer Perceptron (MLP), for assessing agriculture land suitability. The system gathers data from various sensor devices to train the model for evaluating land suitability. With four hidden layers, the multiclass classification accuracy of the MLP model was 92.6%. The suggested method offers decision classifications of more appropriate, suitable, somewhat suitable, and unsuitable, which help farmers assess whether the land is suitable. AI and sensor network technologies make agricultural automation and decision-making possible.

Torres et al. [24] presented the Hydra framework, which represented a multilevel data integration structure that works to make decisions and improve the accuracy of sensors in smart agriculture. Two applications have been developed to facilitate smart water management. The first application aims at soil moisture levels to see if irrigation is necessary, and the second aims at crop output and evaporation to ensure irrigation happens at the right time. The most effective technique for locating and eliminating impacted values combines the Extreme Studentized Deviate (ESD) approach with the weighted outlier-robust Kalman filter (WRKF filter). Furthermore, a quadratic SVM (Support Machine Vector) model was developed for evapotranspiration, resulting in values close to the evapotranspiration reference model (Penman-Monteith). Hydra improves sensor precision in smart agriculture, identifies application target events, and produces more accurate decisions. This approach also offers an inexpensive (IoT) alternative.

Maya Gopal et al. [25] proposed a hybrid Artificial Neural Network and Multiple Linear Regression (MLR-ANN) model for crop yield prediction, where MLR intercept and coefficients are used to initialize the ANN's input layer weights and bias. The hybrid model uses a Feed Forward Artificial Neural Network with a Back Propagation training algorithm. Using performance metrics, the hybrid model's prediction accuracy is compared to other models, including ANN, MLR, Support Vector Regression (SVR), k-Nearest Neighbor (K-NN), and Random Forest (RF). The study's data were gathered from various sources and preprocessed before being fed into feature selection algorithms. The hybrid MLR-ANN model was trained with the features chosen from the feature selection techniques to predict yield. The findings demonstrate that the suggested hybrid MLR-ANN model provides better accuracy compared to traditional models. Lack of knowledge regarding the possible effects of various parameter settings, including the number of hidden layers, number of hidden neurons, and learning rate, on the hybrid MLR-ANN model's accuracy.

Shadrin et al. [26] provided a low-power embedded sensing device with a graphics processing unit (GPU) provides an embedded system with Artificial intelligence (AI) capabilities for in-situ plant leaf growth dynamics prediction and continuous analysis. The Long-Short Term Memory Network (LSTM), a Recurrent Neural Network (RNN), serves as the primary AI model for the system. It discussed how to gather and handle a dataset on tomato growth. There were 400 and 200 elements in each of the training and test sets of the dataset that were used to train and test the LSTM model, respectively. Using Root Mean Square Error (RMSE) to evaluate the accuracy of the predictions for different periods, ranging from 30 minutes to 5 hours. The findings indicate a decent match to the ground truth, with RMSEs for the various solutions for the 5-hour prediction horizon ranging from 9 to 14. Using a typical Li-ion battery, the suggested embedded system with AI allows for 180 days of independent operation. It also makes intelligent monitoring applications possible in the field of agriculture.

Anand et al. [27] suggested an IoT and machine learning system to detect soil moisture and atmospheric components. It gathers information from temperature, rain, and moisture sensors using a Node MCU ESP8266 microcontroller. On the Thing Speak Cloud server, the information is stored. Machine learning algorithms were then utilized to predict the appropriate crop type based on the collected data. The farmer obtained pertinent information to help with decision-making on crop production. The suggested approach can help with crop production decision-making, boost productivity and efficiency, and improve agricultural activities.

Mahmoudzadeh et al. [28] employed machine learning techniques to digitally map soil organic carbon (SOC) in western Iran. There were five machine learning methods used: Support Vector Machines (SVM), k-nearest Neighbor (k-NN), Random Forests (RF), Cubist (CU), and Extreme Gradient Boosting (XGBoost). Predicted the spatial distribution of SOC in the western Iranian region of Kurdistan using 865 soil samples and 101 auxiliary variables. The dataset included temperature readings from ten weather stations in Kurdistan and soil samples from the plow layer (0–30 cm). With an R2 of 0.60 and an RMSE of 0.35%, the RF algorithm had the best performance in predicting the spatial distribution of SOC. Machine learning techniques such as RF offer an unbiased and reliable approach for predicting soil properties, particularly for smaller datasets. Demonstrates how ML algorithms may be effectively applied to the large-scale mapping of SOC and their uncertainty in western Iran, an area characterized by a wide diversity of climate, land use, and topography features.

Zhao et al. [29] presented a proposal for an IoT-assisted Smart Farming Framework (IoT-SFF) that utilizes geospatial analysis and big data analytics for smart irrigation and crop monitoring on an IoT platform. It also incorporates unmanned aerial vehicles (UAVs) for precision agriculture and field management. Discusses wireless sensors in IoT devices for various agricultural applications, including crop status, soil preparation, insect and pest detection, and irrigation scheduling. The simulation findings show that the proposed IoT-SFF model improves the crop yield ratio by 92.4%, prediction ratio by 97.7%, accuracy ratio by 94.5%, average error by 38.3%, and low-cost rate by 34.4%. Using geospatial analysis and big data analytics in the IoT-SFF model allows for precise decision-making, reduced production costs, improved crop quality, and optimal resource utilization in smart agriculture.

Pudumalar et al. [30] proposed a recommendation system for precision agriculture using an ensemble model with majority voting technique, incorporating Random tree, Chi-squared Automatic Interaction Detection (CHAID), K-Nearest Neighbor (K-NN), and Naive Bayes (NB) as learners. The method makes crop recommendations based on site-specific criteria by utilizing research data on soil characteristics, soil types, and crop yield. Based on the farmers' soil needs, the recommendation system aims to offer farmers the best crop based on their soil requirements with a high degree of accuracy and efficiency. Precision agriculture has advantages like lower crop selection errors and higher yield.

Potential challenges, however, can include the requirement for reliable and up-to-data and the initial investment necessary to implement precision agriculture methods. The suggested model exhibits encouraging outcomes in precision and high-accuracy weed detection in crops. It might boost crop productivity and help with weed control in agriculture.

Moso et al. [31] suggested an ensemble anomaly detection method called Enhanced Locally Selective Combination in Parallel Outlier Ensembles (ELSCP). For analyzing temporal, spatial, and time-series data streams in smart agriculture. The process is applied to two case studies' harvest data including combine-harvester GPS traces and crop data. The methodology performs well with an Area Under the Curve of Precision-Recall score of 0.972, which is 58.7% better than the second-best method. Furthermore, there is a direct correlation between crop damage and 30% of the anomalies in the crop dataset. Finding the test instances nearest neighbors takes a lot of time, and performance in a multidimensional space can be improved, mainly if there are a lot of irrelevant attributes or features.

Adkisson et al.[32], presented a proposal to include an unsupervised Autoencoder machine learning model for anomaly detection in smart farming. Data is encoded and decoded by the Autoencoder model, which ignores outliers and identifies anomalous data based on high reconstruction loss values. Data from a planned greenhouse test bed with several sensors in a smart farming setting was used to train and evaluate the model. The suggested Autoencoder model found anomalies in the smart farming data with a 98.98% accuracy rate. The propo9sed model has the advantage of having a high accuracy in anomaly detection and the ability to identify data discrepancies. However, the model takes a long time to train—262 seconds—while it takes a short time to detect—0.0585 seconds.

Junaid et al. [33] proposed an intelligent cloud-based system for monitoring agriculture farms using IoT, where specialists and farmers evaluate stored and real-time data. Accurate data classification is achieved by applying AI-based machine learning models, including SVM. The system collects many data types in significant volumes from multiple sources, including text, images, video, audio, and digital maps. With competing smart farming baselines, the approach works well and achieves performance efficiency in execution time by 14%, throughput time by 5%, overhead time by 9%, and energy efficiency by 13.2%. By utilizing IoTs for remote farm monitoring, the suggested system helps farmers improve their farming skills and have access to pre-disaster recovery information. The system offers specific and general information on international markets related to crops.

Catalano et al. [34] introduced an Anomaly Detection System for smart agriculture using a multi-layered architecture that combines a multivariate linear regression (MLR) algorithm and a long-term memory neural network algorithm (LSTM). This helps the farmer make decisions that will optimize results in quantity and quality, prevent waste, and increase profits. The anomaly detection systems are applied to a real dataset from a smart agriculture system in the Apulia region of Italy. While the LSTM algorithm may identify anomalies on individual sensors, the MLR algorithm evaluates data correlations more effectively and with fewer computational resources. The combination of MLR and LSTM improves anomaly detection accuracy in the innovative agriculture system. Because it is more computationally intensive, the LSTM algorithm cannot correlate measurements from various sensors within the smart agricultural system.

Cheng et al. [35] proposed a new anomaly detection model based on generative adversarial networks (GAN) with an attention mechanism for smart agricultural IoT time series data. The model captures temporal dependence and correlations between features by using a deep learning approach to learn the distribution patterns of standard data. An encoder-decoder structure enhances the model's performance in learning average data. A new reconstruction error calculation method is developed to assess point-wise difference and curve similarity errors. Three datasets related to smart agriculture, SWMRU, Home C, and KDDCUP99, are used to evaluate the proposed model. The proposed model achieves accurate anomaly detection with precision, recall, and F1 score higher than counterpart models, reaching 0.9351, 0.9625, and 0.9482, respectively.

Murugamani et al. [8] introduced a machine learning technique for precision agriculture applications in the 5G-based Internet of Things. It uses image processing-based machine learning techniques, RF, SVM, and NB for detecting and classifying cotton leaf diseases. The suggested system also comprises soil sensing, a smartphone application, and a remote monitoring system to inform farmers. Makes use of data on cotton leaf diseases, soil condition, and plant development parameters. The SVM algorithm exhibits its effectiveness in detecting and controlling cotton leaf diseases, yielding the highest accuracy, 98.34, in recognizing a range of diseases. The proposed method makes accurate disease detection, remote surveillance, and parameter control over agriculture possible. It lessens agricultural risks, promotes intelligent farming, and enhances farmer productivity.

Bakthavatchalam et al. [6] suggested an IoT framework for measurement and precision agriculture, using machine learning algorithms to predict crop recommendations, Multilayer perceptron rules-based classifier JRip, and decision table classifiers are the chosen classifiers for the classification. The classifiers' performance is evaluated, with a maximum model building time of 8.05s and an accuracy of 98.22%. The Kaggle database provided the dataset for the analysis, which included 2200 instances for 22 different crops. The dataset contains seven parameters: temperature, humidity, precipitation, pH, potassium, phosphorus, and nitrogen. Data gathering from large and remote farm areas is made possible by the proposed framework, which combines trending technology and agriculture measurements. Applying machine learning algorithms makes precision agriculture and accurate crop prediction possible.

Kethineni et al. [36] proposed an IoT-based privacy-preserving anomaly detection model for smart agriculture, uses an enhanced deep learning framework based on privacy encoding, including an attention-based gated recurrent unit neural network model for intrusion detection and a sparse capsule-auto encoder for data encoding. The proposed model is compared with existing deep learning models using two public datasets. The performance of the proposed model is evaluated on the ToN-IoT dataset. The proposed model achieves an accuracy of 99.9%, recall of 99.7%, precision of 99.9%, and F1-score of 99.8%. The proposed model has advantages over other traditional deep learning models in terms of classification results, and it can ensure data privacy in Internet of Things-based agriculture. However, the model's operation and training necessitate significant computational resources, which can be costly and time-consuming.

Sangeeta et al. [37] proposed a machine-learning approach to predict the crop with the highest yield in a given area by analyzing weather data such as temperature, humidity, rainfall, soil factors like PH and type, and historical crop-growing data. Based on the gathered dataset, the system creates a prediction model using a variety of machine-learning approaches, including Random Forest, Polynomial Regression, and Decision Trees. Predicted accuracy is used to assess the models' correctness. The Polynomial Regression and Decision Tree models reach 88% and 74% testing accuracy, respectively,

Table 1: Compersion of the Related Works

Paper	Method	Accuracy	Source of Dataset	Purpose
[17]	Semi-supervised learning (ISODATA)	76.42%	Camera	Early warning vegetable pest flea beetle.
[18]	KNN	-	Camera	Classify plant leaves disease
[19]	HWSAN	97%	Sensors	Soil property monitoring and management drip irrigation
[20]	(DN)&CNN	99.5%	Camera	Distinguish weeds from crops
[21]	SVM & K-NN	75%	Camera	Introduce an un manned aerial vehicle (UAV)-based weed mapping system
[23]	k-means	-	Sensors	Anomaly Detection: Identify the general data pattern, sensor anomalies, and sensor faults
[1]	MLP	99%	Sensors	Assessing agriculture land suitability
[24]	ESD method, WRKF filter, SVM	98.7%	Sensor	Smart water management
[25]	hybrid MLR-ANN	98.9%	Camera	Finding accurate yield prediction
[26]	(LSTM) & (RNN)	-	Camera	Provide a plant leaf growth dynamics in-situ prediction and continuous
[27]	Multiple Linear -regression& K-Means clustering	-	Sensors	Predicate crop type based on soil moisture and atmospheric elements
[28]	Cubist, K-NN, Extreme Boost, SVM, RF	99.7%	Sensors	Soil Organic Carbon Prediction
[29]	IoT-SFF with GIS analysis	94.5%	Benchmark	Smart irrigation and crop monitoring on an Internet of Things platform

[30]	Random tree, CHAID, K-NN, Naive Bayes	88%.	Sensors	Increases crop productivity and decreases crop wrong choice
[31]	ELSCP	97.2%	Satellite	identification of anomalies that impact harvest efficiency
[32]	Unsupervised Autoencoder	98.98%	Sensors	Anomaly detection due to device malfunction, accidental disruption, or intentional attacks
[33]	SVM	87%	Multi-source	Monitoring of agriculture farms
[34]	MLR & LSTM	-	Sensors	Anomaly Detection in smart farming systems and reducing potential damage.
[35]	Deep learning	93%	Sensors	Anomaly detection for brilliant agriculture time series data
[8]	RF, SVM, NB	98.34%	Sensors, Camera	Detecting and monitoring diseases affecting cotton leaves
[6]	MLP, JRIP, Decision table	98.22%	Sensors	Control and detect cotton leaf diseases
[36]	Deep learning	99.9%	Sensors	Anomaly detection for privacy-preserving
[37]	Random forest Polynomial regression Decision Tree	97% 88%, 68%	Sensors	Analyzing a variety of climatic elements to predict the best crop in a given area
[38]	Bayes Net, Naive Bayes Classifier, Hoeffding Tree, RF, Multilayer Neural Network	99.59%	Sensors	Crop analysis and preiction
[39]	K-means, CNN	92.89%	Camera	Weed identification

whereas the random forest model achieves training and testing accuracy of 97% and 85%, respectively. Farmers may be able to increase their production by using the suggested system to predict crop yields more accurately. The overfitting problem of decision trees is overcome by ensemble models such as random forests, leading to promising results.

Elbasi et al. [38] proposed applying various machine learning algorithms with different features for crop analysis. The Bayes Net, Naive Bayes Classifier, Hoeffding Tree, Random Forest, and Multilayer Neural Network algorithms were among the carefully selected due to their characteristics and capabilities. Several features, including the ratio of nitrogen content (N), temperature, soil pH, rainfall, humidity, the ratio of phosphorus content (K), and the ratio of potassium content (P), are included in the dataset, which was gathered from the crop recommendation database. The Bayes Net algorithm achieved a classification accuracy of 99.59%, followed by the Naïve Bayes Classifier and Hoeffding Tree algorithms with 99.46% accuracy. Increasing crop yields, decreasing waste, optimizing crop production, and minimizing farm costs are all possible by integrating machine learning algorithms in agriculture. Farmers may make better decisions about the factors influencing crop growth by analyzing a wide range of data gathered from farms and integrating online IOT sensor data.

Tang et al. [39] proposed a weed identification model that combines K-means feature learning with a Convolutional Neural Network (CNN). The random initialization of CNN weights is replaced by a pre-training process called K-means unsupervised feature learning, which enables more reasonable parameter values before optimization. Soybean seedlings and the weeds that grow beside them are the main objects of the study. 92.89% accuracy was attained by the suggested strategy, higher than CNN with random initialization by 1.82% and a two-layer network without fine-tuning by 6.01%. The technique improves the accuracy of weed identification by overcoming unstable identification and weak generalization in feature extraction.

3. Datasets in smart agriculture

A critical aspect of smart agriculture is using datasets to train machine learning models for weed detection, crop yield prediction, and disease diagnosis. These datasets can be collected from various sources, such as IoT sensors, satellite imagery, and manual data collection as shown in Table 2. Machine learning models can then be trained on these datasets to make predictions and provide insights to farmers. Using datasets in smart agriculture is crucial for improving crop management and increasing efficiency in the agricultural industry [40]. For example, **a GPS dataset**. These datasets provide valuable logistics data that aid farmers in making informed decisions and enhancing the efficiency of their operations. For instance, GPS data from a farm in Colorado, USA, was collected using an Android application during the wheat harvesting seasons of 2014, 2016, 2017, 2018, and 2019. The dataset comprises raw GPS data organized into two zip packages, along with some post-processing results. By automatically extracting current, high-level knowledge from GPS recordings, this method enables farmers to make superior logistical decisions.

The Janatahack Machine Learning in Agriculture dataset is a set of data to apply machine learning algorithms to improve agriculture's effectiveness and efficiency. Information on different crops, soil types, and weather conditions are all included in the dataset. The portals Kaggle and Analytics Vishay offer the dataset. This dataset is a part of the broader "smart farming" movement, which aims to incr
+ease agriculture's effectiveness and efficiency by applying high-precision algorithms. The dataset includes the following: Unique ID, estimated number of insects per square meter, crop and soil categories (0,1), type of pesticides used, number of doses per week, number of weeks used, number of weeks not used, season category (1,2,3), and crop damage category.

Crop Recommendation dataset, a dataset that, based on several parameters, would enable users to build a predictive model that recommends suitable crops to grow on a specific farm. The rainfall, temperature, and fertilizer data sets currently available for India were supplemented to create this dataset. The crop recommendation includes parameters necessary for crop prediction, such as temperature, humidity, average rainfall, soil pH, nitrogen need ratio, potassium requirement ratio, and phosphorous requirement ratio. **The V2 plant seedlings dataset** contains 5,539 images of crop and weed seedlings. The images are divided into 12 classes. In Danish agriculture, these classes represent common plant species. RGP photos of plants at various stages of growth are included in each Class. The images are in PNG format and come in different sizes. **Pest datasets**: Images of diverse insects taken at various locations are included in this dataset. In many cases, insects blend in with the crop, making it hard to tell them apart. Hence, identifying pests or even other use cases requiring pest detection can be accomplished using this information. There are insects and crops in this dataset.300 training and 50 testing photos are included in the dataset.

Data from Quality-Controlled Research Weather Data, USDA-ARS Bushland, Texas, Data on 15-minute me a weather from the USDA-ARS Conservation and Production Laboratory (CPRL), Soil and Water Management Research Unit (SWMRU) research weather station in Bushland, Texas (Lat. 35.186714°, Long. -102.094189°, elevation 1170 m above MSL) for every day in 2016 is included in the dataset. These data come from sensors deployed at standard heights over grass irrigated and mowed during the growing season to reference evapotranspiration standards. Sensors are replicated at every height. Using appropriate regression relationships, data from a duplicate sensor can fill in gaps in the primary sensor's data. Sensors deployed at one of the four sizable weighing lysimeters immediately west of the weather station can also fill in gaps. The weather data includes precipitation, wind speed (m/s), sun irradiance (W m-2), air temperature (C), and relative humidity (%). The 15-minute precipitation data for each lysimeter are derived from changes in mass because the large (3 m by 3 m surface area) weighing lysimeters are better rain gages than tipping bucket gages. The land slope is <1% and flat. Winds are usually from the South and Southwest, and the 20-year pan evaporation record indicates about 2,600 mm of Class A pan evaporation annually. The mean annual precipitation is approximately 470 mm. The region has a semi-arid climate with May through September, around 70% (350 mm) of the yearly precipitation and an average of ~1520 mm of pan evaporation.

Soil Sensor Readings

TON_IoT datasets: The TON_IoT datasets are the new generations of (IoT) and Industrial IoT (IIoT) datasets designed to assess the accuracy and efficacy of various AI-based cybersecurity applications. Because the datasets contain heterogeneous data, they have been called ToN_IoT. Gathered from a large-scale, realistic network created at the Australian Defense Force Academy (ADFA), the School of Engineering and Information Technology (SEIT), UNSW Canberra, and the IoT Lab. This dataset comprises a range of recent attack cases found in IoT environments, such as Ransomware, Backdoors, Man-in-the-Middle (MITM), Distributed Denial of Service (DDoS), Denial of Service (DoS), injection, passwords, scanning, Cross-Site Scripting (XSS), and injection. This dataset consists of 43 labeled features, an average vector, and nine different types of attacks. These characteristics are employed in the smart agriculture attack detection process.

BoT-IoT dataset: In UNSW Canberra's Cyber Range Lab, a realistic network environment was designed to create the BoT-IoT dataset. Both regular and botnet traffic were present in the network environment. The source files for the dataset are available in different formats, including CSV files, generated Argus files, and original Packet Capture (Pcap) files. The files were divided into subcategories and attack categories to aid in the labeling procedure. The 69.3 GB collected Pcap files include almost 72.000.000 records. The extracted flow traffic has a size of 16.7 GB in CSV format. DDoS, DoS, Operating System (OS), Service Scan, Keylogging, and Data exfiltration attacks are all included in the dataset. The DDoS and DoS attacks are further organized according to the protocol. Eighty-eight tagged features, four alternative attack types and a standard vector are all included in this dataset. This dataset has fifty thousand data points for testing and forty thousand data points for training.

Table 2: Details of the Agricultural Datasets

Dataset name	Link	Records	Public	Features
GPS dataset	PURR - Publications: Combine Kart Truck GPS Data Archive (purdue.edu)	-	No	7
The Janatahack	https://datahack.analyticsvidhya.com/contest/janatahack-machine-learning-in-agriculture/#DiscussTab	-	No	10
Crop recommendation	Crop Recommendation Dataset (kaggle.com)	2200	Yes	7
V2 plant seedlings	V2 Plant Seedlings Dataset (kaggle.com)	4823	Yes	9
Pest datasets	https://www.kaggle.com/simranvolunesia/pest-dataset	3150	Yes	9
Weather Data	https://catalog.data.gov/%20dataset/data-from-quality-controlled-research-weather-data-usda-ars-bushland-texas	35139	Yes	13
TON_IoT datasets	ToN_IoT datasets | IEEE DataPort (ie-dataport.org)	378,782	Yes	34
BoT-IoT dataset	The Bot-IoT Dataset | UNSW Research	50000	Yes	46
Plant Village dataset	https://www.kaggle.com/datasets/emmarex/plantdisease	54,305 images	Yes	-
Soil Sensor Readings	https://data.melbourne.vic.gov.au/explore/dataset/soil-sensor-readings-historical-data/information/	2,060,917	Yes	24

4. Challenges of AI applications in smart agriculture

The integration of Artificial Intelligence (AI) in smart agriculture has shown significant promise in enhancing crop yields, optimizing resource utilization, and improving overall agricultural efficiency. However, several challenges persist in the widespread adoption and effective implementation of AI in this domain. Here are some of the key challenges [41].

- **Data Quality and availability:** Effective AI systems require vast amounts of high-quality data. In agriculture, obtaining such data can be difficult due to the variability in environmental conditions, crop types, and farming practices. Inconsistent or incomplete data can hinder the accuracy and reliability of AI models [42]. The availability of data is another significant challenge. Agricultural data is often scattered across various sources, and integrating these sources can be complex and time-consuming.
- **Cost and accessibility:** The implementation of AI technologies can be expensive, involving the cost of advanced equipment, software, and training. Small and medium-sized farms may find it challenging to afford these initial investments. Ensuring the accessibility of affordable AI tools and technologies to farmers of all scales is crucial to avoid creating a technological divide in agriculture [43].
- **Lack of Technical Expertise:** The deployment and maintenance of AI systems require specialized knowledge and skills. Many farmers may lack the technical expertise needed to operate these systems effectively. This gap necessitates comprehensive training and support services, which can be resource-intensive[44].
- **Scalability Issues:** AI solutions developed for one type of crop or farming practice may not easily scale to others due to the specific requirements and conditions of different agricultural sectors. Customizing AI applications for various contexts can be time-consuming and expensive [45].
- **Environmental Variability:** Agricultural environments are highly dynamic and influenced by numerous factors such as weather, soil conditions, and pest populations. AI systems must be robust enough to handle this variability and provide reliable recommendations under changing conditions [45].

5. Challenges in IoT-Based Agricultural Systems

- **Concerns on Cost:** The price of implementing IoT in agriculture can be broken down into development and maintenance costs and hardware and software costs, including the cost of purchasing devices and sensors. Reducing system costs and development and maintenance expenses are critical since farmers need help implementing IoT technology due to the high cost of hardware and software. Energy management is also crucial to making IoT-based innovative agriculture applications more sustainable; exploring energy harvesting solutions, including solar, wind, and biomass, can help [46].

- **Concerns on the system**: Agriculture systems must adapt to various environmental conditions, but hardware problems and environmental changes might compromise real-time data accuracy. To lessen the impact of climatic fluctuations in agricultural systems, sophisticated cloud detection and atmospheric correction techniques are essential. In agriculture systems, hierarchical architecture is more efficient for large-scale deployment than flat network architecture, and platforms and solutions should be more accessible to farmers. To prevent post-deployment losses, real-time analysis is essential before system deployment [46].
- **Concerns on Data:** Since incorrect readings can significantly reduce system reliability, reliability is a crucial problem for IoT devices regarding data transmission. System failures, battery issues, and other interventions are challenges to data integrity. Another issue is data storage because sensors produce data continuously and need a lot of resources for analysis. The need for more storage leads to the development of sophisticated software platforms and facilities for the scalable management of significant data sources. An Internet of Things (IoT)-based agriculture system may cause various faults, making fault tolerance crucial for wireless sensor networks [46].
- **Concerns on devices:** Device standardization is critical for widespread technology use, yet more standard formats for data processing need to be developed, resulting in different outputs and interoperability issues. The development of 5G networks enables faster connectivity between devices and servers, making it perfect for sending information from remote sensors and meeting users' requirements for

secure and rapid data transfer. Lack of interoperability in smart agriculture inhibits the adoption of new technology and reduces crop productivity, emphasizing the significance of integrating diverse machine communication standards and maintaining equipment availability in various environments [46].

6. Challenges related to the usage of ML in agriculture

- **Interpretability:** It can be challenging to analyze the outcomes of machine learning models, especially when those models employ complicated deep learning approaches. Farmers may need help understanding the elements in predicting a particular crop or recommendation [47].
- **Accessibility:** Accessing the hardware and software infrastructure needed for creating and implementing ML models in situations with restricted resources may be challenging [47].
- **Privacy and security:** These worries are related to gathering, storing, and utilizing sensitive agriculture data. Maintaining security and privacy while permitting access to the data for machine learning research can be difficult [47].
- **Human factors:** Farmers and other interested parties could require more time to be ready to adopt new methods and technological advancements like machine learning-based systems. Technology must be made accessible, easy to use, and capable of offering significant advantages to be employed more extensively [47].

7. Conclusion

In summary, the survey emphasizes how new technologies, like smart agriculture, are changing farming to meet the growing demand for food as the global population increases. Traditional farming methods are being replaced by smart agriculture, which uses advanced technologies such as the IoT and AI to make farming more efficient and effective. AI helps farmers make better decisions and accurately manage crops, especially machine learning. The survey discusses how smart agriculture is being used to monitor crops, detect problems, and improve farm security. While these advancements offer great promise, challenges still need to be addressed for smart agriculture to reach its full potential. Overall, the survey sheds light on the exciting changes in agriculture and the opportunities and obstacles that come with them.

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