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Review Manuscript

Comprehensive Survey on Applications of Internet of Things, Machine Learning and Artificial Intelligence in Precision Agriculture

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ABSTRACT

A comprehensive, multidisciplinary analysis of the latest developments in digital agriculture is conducted with the use of artificial intelligence (AI), machine learning (ML), and the Internet of Things. By automation and the use of modern, scalable technology solutions that reduce risks, support sustainability, and give farmers predictive advice, traditional agricultural processes are being updated and improved to maximize production. In this paper, the applications of AI, IoT, and ML in agricultural production systems are discussed in detail. The applications that have been explored can be broadly categorized into three areas: soil management, livestock management, and crop management. Weed detection, disease identification, and yield forecasting are some of the applications for crop management. Two applications of livestock management are animal welfare and production. The use of AI, IoT, and ML will make it possible to collect data from agricultural activities for analysis and the extraction of insightful knowledge, facilitating prompt and accurate decision-making to increase agricultural productivity. This will result in farming that is more exact and efficient while requiring less labour and producing high-quality produce.

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INTRODUCTION

The agriculture industry plays a major role in the economic growth of any given nation. With population growth, climate change occurring more frequently, and resources becoming scarce, it is becoming more challenging to feed the world's population. A cutting-edge method to solve current concerns with agricultural sustainability is smart farming, often known as precision agriculture. According to Fountas *et al*., 2020, the technology's revolutionary motor is machine learning, or ML. It can now be used to teach the machine without explicit programming. Machine learning and farm equipment with Internet of Things (IoT) capabilities will be major forces behind the next agricultural revolution.
The digital revolution is changing agriculture by using information and communication technologies (ICTs) to increase production and decision-making

through automated tools, sophisticated technology, and ICTs. Increased yields, cheaper prices, and fewer environmental effects are the outcomes of emerging technologies in agriculture, including robotics, artificial intelligence, machine learning, big data analytics, remote sensing, and the Internet of Things (IoT). Data-driven solutions open the door to production potential that is sustainable and resource-efficient. Technologies for managing precision agriculture enable growers to profit from the recent big data revolution. Systems for data mining sift through enormous amounts of data in search of trends and answers. They assist farmers in managing the unpredictability of their agricultural systems by adjusting inputs to produce the intended outcomes (Fountas *et al*., 2020). Devices on farms can now remotely measure a variety of data kinds thanks to the Internet of Things, and the farmers may get this information instantly. Proximal sensors, drones, and satellites are examples of agricultural remote sensing technology (Oza *et al*., 2008).

These sensors enable early decisions on fertilization, irrigation, and pest control by utilizing the reflectance characteristics of plants to determine biomass, yield, acreage, vegetative vigor, drought stress, and phenological development. Since very high-resolution satellite data with different viewing geometry, techniques, spatial resolutions, and spectral ranges are commercially available, new views on the use of earth observation products in agricultural monitoring have emerged (Oza et al., 2008). Remote sensing instruments that operate at low altitudes, such as Unmanned Aerial Vehicles (UAVs), can gather comparable data. These devices capture a broad range of electromagnetic spectrum using thermal, hyperspectral, and multispectral cameras. These photos have a far lower coverage area than satellite products, despite the fact that data retrieval is less weather-sensitive.

IoT data, such as multispectral sensors and satellite data hubs, is used by machine learning algorithms to create machine learning models. Machine learning techniques use training data to teach algorithms how to accomplish specific tasks. A practice-enhancing performance indicator is used to assess the effectiveness of a task-specific machine learning model. ML models and algorithms are assessed using a variety of statistical and mathematical approaches. The trained model can be applied to test data to perform classification, prediction, or clustering after the learning process (Liakos *et al*., 2018). Supervised and unsupervised learning are the two types of learning that occur in machine learning. The learning models are divided into four categories: dimensionality reduction, regression, clustering, and classification. Artificial intelligence (AI)-enabled solutions use machine learning algorithms in conjunction with data from IoT sensors for predictive analytics and precision farming.

Despite any conventional perceptions people may have of agricultural practice, agricultural science diligence today is more exact, precise, data-driven, and aggressive than ever. Nearly every industry, including "smart agriculture or precision agriculture," has been transformed by the Internet of Things (IoT) technologies other examples include smart cities, smart health, smart grids, and smart homes (Liakos *et al*., 2018), and (Mustafa *et al*., 2021). To boost the amount and quality of crop and animal production from farmland to meet the rising food demand, machine learning would be applied by utilizing IoT data analytics in the agricultural industry (Mustafa *et al*., 2021). These groundbreaking discoveries rely on conventional farming practices and offer the greatest prospects, but they also have a number of disadvantages. Precision agriculture strives to achieve optimal results from precise inputs by arming farmers with technology. Smart sensors, actuators, robotics, drones, satellite images, and other significant technological advancements have all been made possible by the Internet of Things (IoT), which has helped the agricultural sector expand (Mustafa *et al*., 2021). These elements are crucial and play a Critical role in gathering real-time data and making decisions accordingly without human assistance. artificial intelligence. The automation of intelligent behaviour, which benefits our world and aids farmers in numerous ways and features of the crop and animal yield production.

The Fourth Industrial Revolution (4IR) in agriculture has resulted in several innovations, which are together referred to as precision agriculture. Modern technology makes it possible to operate precisely, efficiently, and effectively process all data, among other things that will elevate agriculture to a new level. Accuracy and correctness are implied by the term "precision agriculture" (Liakos *et al*., 2018). With the premise of carrying out interventions in the correct place, with the right intensity, and at the right time, precision agriculture's primary goal is to adapt operations to the actual geographical conditions and aid to guarantee global food security (Mustafa *et al*., 2021).

One of the modern farming methods, precision agriculture gathers, processes, and analyses data to increase agricultural yield while consuming less resources. Agriculture contributes significantly to the Gross Domestic Product (GDP) of our country. Precision agriculture uses wireless sensor networks (WSN) and the Internet of Things (IoT) to build smart farm management systems (Madhumathi, et al., 2022). Farmers may access field data instantly thanks to the Internet of Things (IoT) in agriculture through the usage of decision support tools. IoT technologies in agriculture change the game since they monitor and send data without the need for human intervention. Agricultural IoT systems are built using sensors and actuators that sense and respond to a variety of inputs and provide instantaneous feedback (Madhumathi, *et al*., 2022).

The goal of precision farming is to maximize crop yields while minimizing the amount of resources used. It involves performing agricultural operations accurately and responsibly. Sensor nodes are positioned in the fields to gather data about the farm and analyse it analytically in order to boost crop productivity (Madhumathi, *et al*., 2022). The base station, which connects these nodes, relays the gathered data to the primary server and then to other platforms for processing and archiving. Additional data processing and machine learning techniques are applied to gain insight from the data.

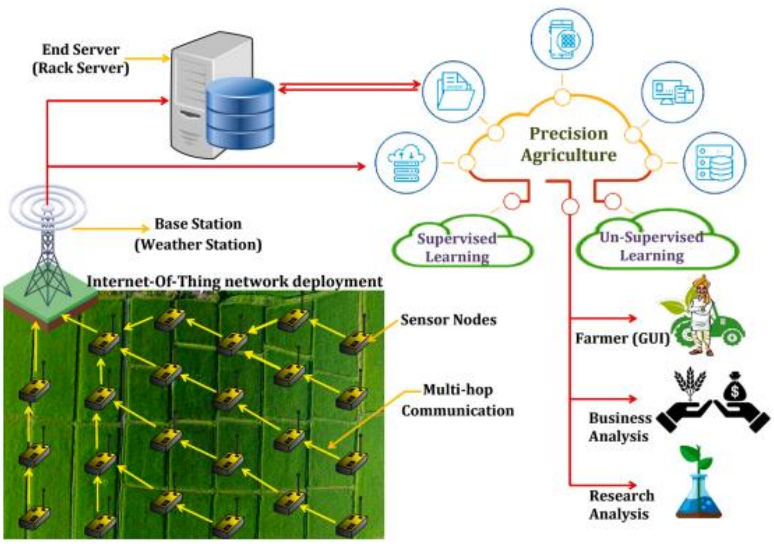

Figure 1: Overview of Major Components in Precision Agriculture (Madhumathi, *et al*., 2022).

Additionally, Precision agriculture, often known as digital agriculture or data-driven sustainable farm management, is a technology-enabled sustainable farm management approach. Basically, it involves implementing contemporary software tools, embedded smart devices, and information technologies for Figure 1 depicts agricultural decision-support systems aiding in precision agriculture (Sharma *et al.*, 2020).

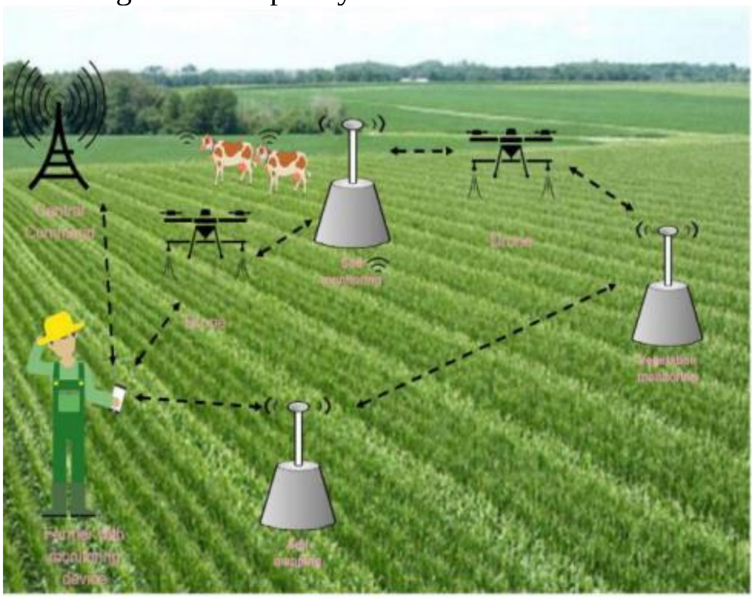

Figure 2: Precision Agriculture Overview (Sharma *et al*., 2020).

METHODS AND MATERIALS

Literature Review

Agriculture has numerous difficulties ranging from Crop disease infestations, poor storage management, pest, and weed control, and ineffective irrigation systems are a few of them. The population of the globe is growing quickly, and with it, so does the demand for food. Farmers' traditional methods of dealing with agricultural problems are unable to meet the growing demand. IoT, machine learning, and artificial intelligence can help with these challenges by maximizing production to meet the growing demand. The applications of artificial intelligence, machine learning, and the internet of things in precision agriculture are reviewed in the following literature.

Internet of Things Applications for Precision Agriculture

Smart Irrigation Techniques

Water is a scarce resource that has an impact on agricultural output because it is required for crop growth and development. Water requirements vary due to the agricultural growth cycles of various crops. Using IoT, proper irrigation methods may be selected, hence reducing flood irrigation and solving water scarcity. This in turn improves crop lodging resistance as well as productivity. In Khriji, *et al*.,2021 a cloud-based smart irrigation system was designed. This system uses sensors to collect moisture data from the soil, then transfers the data to the cloud via an Arduino, where it is stored and farmers access the data through a mobile application. The information proprietor makes an order, and the fundamental activity is done based on the results. The method ensures efficient use of water and saves farmers time by allowing remote monitoring of their fields; nevertheless, its large-scale implementation would be more expensive. Hou *et al.*, 2012 designed an intelligent irrigation system for orchards that considers both the large-scale development paradigm of modern orchards and the precision agricultural construction needs. The system used ZigBee Wireless

Sensor Networks (WSN) to communicate data to the gateway, which then sent the data to the cloud through GPRS. This system covers a broad area, making it suited for large-scale implementation, and the sensor nodes consume less energy.

In view of recent advancements in IoT and WSN technologies that can be utilized in the construction of these systems to support precision agriculture, (Garcia *et al*., 2020) provided an extensive assessment with the goal of summarizing the present state of the art concerning smart irrigation systems. Irrigation systems' monitoring of soil characteristics, weather, and water quantity and quality were the variables selected. An overview of the most widely used wireless technologies and nodes, along with their pros and cons, was also provided.

Environmental Parameter Monitoring

Environmental factors that are vital to crop growth are monitored via sensors. The air temperature, humidity, light intensity, soil temperature, and soil pH are these characteristics. The sensors then send the data they have acquired to the cloud. ZigBee ad hoc network technology was used in (Li *et al*., 2021) to gather information from several sensor nodes in the WSN. This allowed for the real-time collection and upload of environmental data, including carbon dioxide, temperature, and humidity. By reducing disease and insect pests, this approach minimizes the need for pesticides and fertilizers while still providing high-quality produce.

For a farm, (Hwang *et al*., 2010) created an environmental monitoring system that uses GPS, WSN, and solar power to gather, transmit, store, and evaluate agricultural environmental data. The sensor nodes of the system have a long lifespan due to energy collection, which allows them to produce high-quality food without being limited by battery use.

A precision agriculture decision support system was created by ref where a network of Internet of Things devices with sensors for soil moisture, temperature, and air quality Rain was prepared to gather real-time moisture information about a field to make the best crop decision, Akhter, 2021 This research helped to increase crop output by maximizing the use of fertilizers and water. Akhter, 2021 also proposed an IoT framework in the area of precision agriculture, Different sensors were used by the proposed system to measure soil moisture, temperature, and humidity. All of these sensor data were downloaded via a raspberry pi and immediately uploaded to a cloud server, where the readings are further evaluated to raise crop productivity.

Livestock monitoring

Farmers may ensure their animals' health by using sensors to gather data from them about their physiological and nutritional status. A ZigBee-based system for monitoring animal health has been developed (Kumar and Hancke, 2014). It can identify vital information about the monitored animal, including its environment, chewing habits, body temperature, heart rate, and temperature. It can also assess the values detected based on indices of humidity and temperature.

For effective grazing and pasture management conditions, it is crucial to comprehend the mechanisms by which livestock grazing behavior modification is enabled (Singh *et al*., 2019) (Vrchota, 2022). Monitoring the animal is crucial, and it also makes accurate grazing management easier. Small adjustments in location, feeding strategy, or other behaviors can have a significant effect on the flock's overall health and welfare if each animal in the flock is closely observed. When an animal behaves differently than what is deemed "normal" for that specific animal, the farmer is alerted and can take the necessary action.

Agricultural Uses of Artificial Intelligence and Machine Learning

Yield Prediction

Accurate prediction of agricultural yields before harvest offers significant benefits. It empowers farmers to reduce production costs and increasing crop yields. This foresight in turn is invaluable for governments as it enables them to proactively develop programs, transportation logistics planning, establish sound purchasing mechanisms, allocate storage capacity and manage the nation's financial liquidity before crops reach the market, Sinwar et al., 2020. The research by Aggarwal *et al*, 2021 presented a novel ML application for efficiently counting coffee fruits on trees in a non-destructive manner. The system not only automates the counting process but also divides the fruits into three categories: harvestable, not harvestable and those at an irrelevant stage of maturation. Furthermore, the approach calculates the weight and maturity percentage of the fruits. This provides the coffee farmers with useful information for optimizing economic returns and effectively managing agricultural operations. Lu *et al*., 2018 developed a novel algorithm for detecting immature green citrus fruits in the tree canopy in real outdoor environments. This method included two approaches: shape analysis to improve fruit detection and texture to reduce false positives. The study aimed to provide growers with early yield forecasts, allowing them to make informed decisions about site-specific grove management, thereby increasing both fruit production and profitability. In (Ali *et al*., 2016) the scientists developed models that predict grassland biomass using multiple linear regression (MLR), artificial neural network (ANN), an adaptive neuro-fuzzy inference system (ANFIS). The simulations were based on data gathered by space-borne sensors. (Ramos *et al*., 2017) proposed a method for detecting tomatoes in fields using unmanned aerial vehicle (UAV) equipped with cameras capturing red-green-blue (RGB) images. Their approach used techniques like Bayesian information criterion (BIC), Expectation Maximization (EM), self-organizing map (SOM). Table 1 below summarizes the above yield prediction papers.

Table 1: Yield prediction Table

Article	Crop	IoT Hardware	Model	Results
Ramos *et al*., 2017	Coffee	The camera of a mobile device	SVM	ripe:82.5–87.8% Semi-ripe:68.25–85.3% Unripe:76.9–81.3 %
Sengupta *et al*., 2016	Lemons	Camera	SVM	80.4% accuracy
Scurlock, 2002	Grass	Spaceborne sensors	ANN ANFIS	Moorepark: R2 = 0.85, RMSE = 11.07 Grange: R2 = 0.76, RMSE = 15.35
Senthilnath *et al*., 2016	Tomatoes	Camera using UAV	Clustering EM	Recall: 0.6066 Precision: 0.9191 F-Measure: 0.7308

Disease Detection

Pest and disease control is a significant challenge in agriculture, both in open fields and greenhouses. Traditional approach relies on regular spraying of insecticides across entire crop area. While effective, this approach has significant financial and environmental drawbacks. These include pesticide residues in crops, groundwater contamination and harm to local wildlife and ecosystems. Precision agriculture provides a promising alternative, integrating IoT, machine learning, and artificial intelligence (AI) to optimize pesticide application based on specific demands and real time data. This section discusses how this combination of technologies can be used for disease detection in crops. (Truong *et al*., 2017) proposed an IoT-based system for detecting agricultural fungal diseases. This system comprises of multiple sensors that collect real-time environmental data which is then transmitted to the cloud for storage and analysis. The system utilizes a SVM algorithm to predict weather conditions based on collected data. Furthermore, the authors highlighted the potential of Integrating IoT with image processing for more accurate disease detection. (Ebrahim *et al*., 2017) Investigated the use of SVM to detect thrips in crop canopy photos. A novel image processing technology was used to detect possible parasites on strawberry plants. These parasites were subsequently classified using SVM method which incorporated a modified kernel function. (Krishna *et al*., 2019) Implemented a system to detect different plant diseases and automate responses. Image recognition is employed to identify various plant diseases and upon detection, an SMS alert is sent to the farmer, the system triggers pesticide spraying automatically using NodeMCU ESP8266. The system leverages transfer learning, a technique which has also been employed in the studies conducted in (Ramcharan *et al*., 2017), Too *et al*., 2019. Transfer learning is a technique that pre-trains a model on a large dataset and then fine-tunes it for a specific task like plant disease detection. (Hasan *et al*., 2021) demonstrated that transfer learning outperforms a CNN model trained from scratch on smaller datasets. Another model is the Neural Network (NN), which is widely used and recommended for plant disease identification. Inspired by the human nervous system, NN can learn and generalize patterns, making it more effective for analyzing complex data like hyperspectral images. Studies presented by Zhu *et al*., 2017 shown that NNs can achieve a higher accuracy compared to other ML models in diagnosing TVM. The Back-Propagation Neural Network (BPNN) model obtained 95% accuracy, while the chemometric models achieved 80%. Using a new pattern recognition technology called the Artificial Intelligent Nose, it is feasible to build pattern recognition methods like random forest and support vector machines.

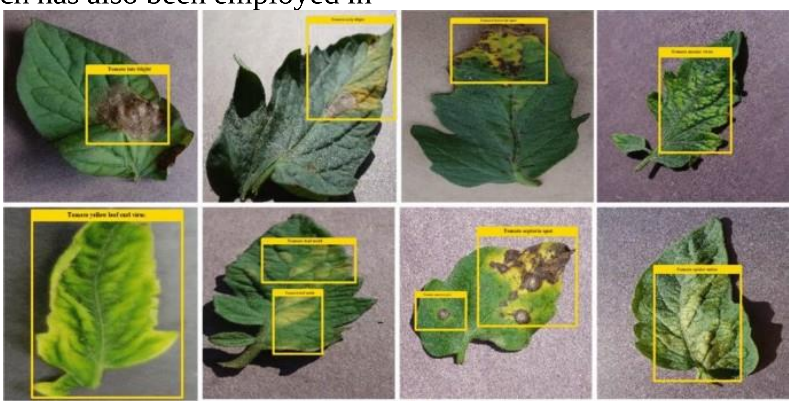

Figure 3: Disease Detection using ML (Nawaz, 2022).

Weed Detection

Weed control which is often cited as the main crop hazard by many farmers remains a significant challenge in agriculture. Distinguishing weeds from crops is crucial for sustainable practices. Again, ML algorithms and sensors can accurately detect and distinguish weeds cost effectively without environmental harm. Leveraging ML for weed detection can significantly reduce herbicides dependance by facilitating tools and robots to remove weeds. Several studies demonstrate the potential of this approach. Liakos *et al*., 2018 developed a novel approach for identifying Silybum marianum, a weed that is difficult to eradicate and known to decrease crop yields. Pantazi *et al*., 2017, employed ML and hyperspectral imaging to develop a system for crop and weed identification. The focus was mainly to detect maize (Zea mays) as a crop plant and Ranunculus repens as a weed for economic and environmental reasons. In another study (Pantazi, *et al*., 2016), scientists used SVM to detect weeds in grassland crops. Table 2 below summarizes the above weed detection papers.

Table 2: Weed detection Table

Paper	Functionality	Model	Result
Liakos *et al*., 2018	Silybum marianum detection and mapping	ANN/CP	98.87% accuracy
Pantazi *et al*., 2017	Identification of Zea mays and weeds	ANN SOM MOG	Zea mays: SOM = 100%, MOG = 100% Weed species: SOM- 53–94% accuracy MOG = 31–98%
Pantazi, *et al*., 2016	Grass vs. weed classifications performance reporting	SVM	97.9% Rumex classification6 94.65% Urtica classification 95.1% mixed weed and weather

Figure 4: Weed Detection in Fields (Pantazi, 2016)

Crop quality

Machine learning is also being used to identify and classify various elements of crop quality, resulting in higher prices and less waste as in the studies conducted by Klompenburg *et al*., 2020); Ramesh, 2020; and Binch *et al*., 2017. A study by *Zhang et al*., 2017) developed a method for identifying and classifying foreign materials trapped in cotton lint during harvesting. The study's goal was to increase quality and minimize fiber damage. Another study (Hu *et al*., 2017) employed an integration of ML and hyperspectral imaging to distinguish between types of Korla pears based on their calyx characteristics. The authors of (Maione *et al*., 2016) presented a method using ML on chemical components to predict and classify the geographical origin of rice samples from two distinct regions in Brazil. Their research identified four key chemical elements crucial for this classification; Cd, Rb, Mg, and K.

Livestock Management

The application of IoT, ML, and AI in livestock falls in two sub-categories; animal welfare and livestock production. Animal welfare is concerned with the health and welfare of animals, with IoT, ML, and AI being used to monitor animal behavior for disease diagnosis. In livestock production, the main scope of IoT, ML, and AI applications is to provide farmers with accurate insights and predictions of economic balances for farmers based on production line monitoring.

Animal welfare

In the first study (Dutta *et al.*, 2015) , data gathered by wearable collar devices with magnetometers and three-axis accelerometers are used to classify cattle behavior and predict estrus cycles, as well as detect changes in feeding patterns. It was proposed in the second paper (Pegorini *et al.*, 2015) to identify and classify chewing behaviors in calves. The scientists constructed a system using ML to combine data from food supplements like hay and ryegrass chewing with behavior data like ruminating and inactivity. Optical FBG sensors were used to collect data. Another work (Matthews *et al.*, 2017) proposed an automated ML based system to track animal activities like standing, moving, feeding, and drinking.

Livestock production

This section explores how ML can be used to enhance livestock production economic efficiency. In this category, three articles deal with cattle and one with eggs. (Yerima, 2005) advocated utilizing milk fatty acids to predict rumen fermentation trends. To properly anticipate rumen fermentations, which are critical for evaluating milk output diets. In this investigation, milk fatty acids accurately predicted rumen volatile fatty acid molar ratios. The following study (Liakos, 2018) proposed an SVM-based technique for early detection and warning of potential issues in commercial egg production, allowing for timely intervention and improved efficiency. A method for calculating bovine weight trajectories over time was developed (Im *et al.*, 2015). Weight estimation is critical for breeders. Derived from SVR models and zoometric data, the last section predicts carcass weight for beef cattle of the Asturiana de Los Valles breed. The technique can predict carcass weight 150 days in advance. (Wang *et al.*, 2018) used convolutional neural networks (CNNs) to recognize pig faces in digital pictures. Researchers wanted to identify animals without employing RFID tags, which cause stress to animals, have a limited range, and take time to scan.

Table 3: Livestock production

Paper	Functionality	Hardware	Algorithm	Results
Dutta *et al.*, 2015	Cattle behavior classification	Three-axis accelerometer and magnetometer	Bagging with tree learner	96% accuracy
Pegorini *et al.*, 2015	Calves' chewing patterns identification and categorization	Fiber Bragg Grating sensors	Decision Tree	96% accuracy
Matthews *et al.*, 2017	Animal tracking and behavior annotation of pigs for welfare and health monitoring	Cameras	Gaussian Mixture Models	Animal tracking: MOTP = 0.89 accuracy behavior annotation: feeding: control R_2 = 0.86, treatment R_2 = 0.49

Soil Management

Good soil management meets essential plant needs. Plants need to have access to the required quantities of water, nutrients, temperature, and oxygen (Yerima, 2005) . Soil data can be collected using wireless sensor nodes put on-site. The collected data can then be incorporated into supervised Machine Learning algorithms to predict and analyze soil properties, as well as identify soil types. The agricultural soil properties which can be predicted include; soil moisture content, temperature, and soil drying conditions (Liakos, 2018) Soil properties prediction and identification is important because it influences crop selection, seed selection, land preparation, fertilizer or manure type selection, and crop yield (Beck *et al*., 2006) , which reduces unnecessary fertilizer expenditures, eliminates the need for soil analysis experts, increases profitability, and improves soil health. (Wang *et al*., 2016) deployed Extreme Learning Machine (ELM) to predict nutrient levels in soilless cultivation, reducing reliance on manual measurements. The model was used by the authors to calculate the amounts of SO_2 4 and H_2PO_4 in a nutrient solution. The authors reported an average RMSE for SO_2 4 predictions of 1.2414 and 0.8892 for H_2PO_4 predictions of 0.8892. Park S (Im *et al*., 2016) used machine learning techniques to estimate soil moisture using MODIS data. AMSR2 soil moisture data were downscaled to 1KM using Random Forest (RF) and Cubist algorithms. These algorithms were used to determine soil moisture levels. The machine learning results were compared to the statistics results of regular least squares. The machine learning model had an R_2 of 0.96 and a root mean squared error of 0.06, whereas the statistical ordinary least squares model had an R_2 of 0.47 and a root mean squared error of 0.16.

Proposed Approaches in The Integration of IoT ML and AI in Precision Agriculture

It is crucial to incorporate and employ cutting-edge procedures and strategies to study the many options for enhancing productivity because the economy of the majority of developing countries are based on agriculture and have diverse climatic conditions. The combination of the Internet of Things (IoT), Machine Learning (ML), and Artificial Intelligence (AI) provides farmers with new tools and approaches for sustainable and effective farming, even with limited resources. These advances open up options like predictive analytics, weather forecasting for agriculture, remote equipment and crop monitoring, smart logistics, and warehousing (Im *et al*., 2016). While farmers have extensive agricultural knowledge, successfully incorporating this new technology requires collaboration. User-centered design concepts ensure that the development of IoT, machine learning, and artificial intelligence applications aligns with with farmers' goals and supports seamless integration into their existing practices. Distributed computing paradigms, such as edge and fog computing, offer efficient and scalable solutions for building the underlying infrastructure which include; IoT architecture, operational rules, and smart processes (Sladojevic *et al*., 2016). These technologies are suggested for a communication architecture. The goal is to assist farmers in creating intelligent systems for both new and existing facilities which can increase both crop and animal yield through the use of precision agriculture.

Discussion and Challenges

The reviewed studies employed various remote sensing technologies for agricultural applications and these include; space-borne sensors, RFID tags, and UAVs fitted with cameras. The space-borne sensors offer a wide coverage but their performance can be affected by weather conditions. RFID tags enable individual identification and tracking of animals. UAVs equipped with cameras provide high resolution data for localized monitoring. Machine learning models played a significant role in these studies with eight different models being used. Five models from the eight were applied to crop management applications, four models were used for livestock management applications and four models were employed for soil management purposes. SVM emerged as the most frequently used technique from the eight. Additionally, the studies explored deep learning techniques for agricultural applications which included CNNs and ANNs (Sladojevic *et al*., 2016), (Abioye et al., 2022).

In a related case study related to precision agriculture, a sensor network system was implemented in which every piece of equipment is connected to Raspberry Pi models zero and three B, as well as a channel, is made to examine how the soil behaves and the atmosphere. The study's network prototype made use of current information on soil conditions (temperature, moisture) and atmospheric conditions (temperature, humidity) (Kamath *et al*., 2019). The read-out number of the Raspberry Pi 3B collected data from various sensors. used to publish, together with another Raspberry Zero device the ThingSpeaks readings on the cloud server. An online platform called ThingSpeak offered analytical data services for Internet of Things applications. The suggested use case demonstrated that it is a practical and affordable method for sending field data to remote servers and analyzing the behavior of the crop and field (Kamath *et al*., 2019). In (Kamir *et al*., 2020) machine learning models were used to identify the hotspots of the yield difference in wheat production. Between 2009 and 2015, academics used data from many sources to produce very high-resolution yield maps. Data was acquired from a variety of sources, such as: The MOD13Q1 data set was used to gather the following information: (a) NDVI time-series data for the entirety of Australia; (b) rainfall and temperature data from historical climate data at the Australian Bureau of Metrology; and (c) maps for observed grain yield obtained directly from intelligent harvesting equipment. The machine learning models employed in the wheat yield prediction study by included k-Nearest Neighbors (k-NN), Random Forest (RF), XGBoost, Multilayer Perceptron (MLP), Support Vector Regression (SVR), Gaussian Process, and Multivariate Adaptive Regression Splines (MARS). This highlights the diverse range of machine learning techniques applicable in agricultural contexts. The authors combined predictions from each of the algorithms into one to achieve prediction optimization (Beck *et al*., 2006). Researchers were successful in estimating the yield with an R_2 of 0.77 and an RMSE of 0.55 using SVR with RBFNN, outperforming the other techniques. The findings were validated using 10-fold cross-validation procedures across the whole dataset, and they significantly enhanced precision agriculture in wheat output.

There is a clear indication that employing artificial intelligence, the Internet of Things, and machine learning in precision agriculture can change a lot of things and help in yield prediction by estimating the crop production to be rewarded to the farmer, disease and pest detection in field crops as well as livestock in their early stages. The weed detection and control, the soil management principles with the techniques in practice induce precision agriculture which has more benefits to the farmer in this digital era. Further to that livestock production and animal welfare are analyzed both by using ML techniques. Machine Learning and the Internet of Things on big data have opened up new avenues for achieving precision agriculture objectives due to the openness of datasets as it makes ML modeling easier, including training and mass prototyping. Hosting, growing, and operating an ML Model on top of relevant datasets is referred to as mass-manufacturing of a prototyped ML Model in Precision agriculture which in turn improves production and yield (Craninx *et al*., 2008). In-production machine learning models must also be resilient and adaptable to future adjustments and input (Craninx *et al*., 2008). The agricultural sector is embracing the digital revolution, mirroring the trend across various industries. This shift involves collecting vast amounts of farm data through wireless networks, IoT devices, robotics, and AI systems. The key lies in harnessing the power of artificial intelligence algorithms, which can sift through this data deluge and extract valuable insights and knowledge to empower informed decision-making and optimize agricultural practices. (Murugamani *et al*., 2022) explored how AI can identify diseased plant leaves. Their research focused on analyzing different components of infected leaves to accurately detect and categorize various plant diseases. This approach not only identifies the disease but also paves the way for automated solutions like targeted pesticide application and user notification, (Al-Hiary *et al*., 2011). demonstrated the effectiveness of the SVM algorithm in disease detection and control, achieving an impressive accuracy of 98.34% for diagnosing bacterial blight. These advancements highlight the potential of AI and machine learning in revolutionizing disease management practices and improving overall farm efficiency. There are various scientific obstacles to the development of ML, IoT, and AI techniques in precision agriculture. For example, (i) developing models that not only diagnose diseases in crops and animals but also prescribe appropriate solutions for prevention and control; (ii) Integrating data and models related to grazing, animal health, plant health and pest control to achieve a comprehensive understanding of the agricultural ecosystem; (iii) Enabling machine learning models to autonomously perfom data analysis tasks and learn from experience, reducing reliance on human intervention; and (iv) integrating soil management and pasture variables because the variables used for both animal health and animal grazing are only behavioral and environmental. Further, the lack of small resource-constrained embedded sensors for data collection is not precise and needs huge machines for ML algorithms processing (Morales *et al*., 2016). The future of this work lies in deploying real-time machine learning, artificial intelligence, and IoT models within the agricultural sector. These models aim to solve potential challenges faced by farmers in the agriculture sector with better accuracy to help increase productivity for both livestock and crop yields.

CONCLUSION AND RECOMMENDATION

This work has explored the integration of IoT, remote sensing data, machine learning models and Artificial Intelligence in precision agriculture. The primary goal is to optimize production by leveraging AI systems that provide comprehensive and insightful guidance for informed decision-making. Consequently, it is projected that the use of IoT, ML, and AI in agriculture will increase over the coming years, allowing for the development of integrated and practical systems. Precision farming aims to increase yields through precise inputs, empowering farmers with advanced technology. Key advancements in this sector include intelligent sensors, actuators, satellite imagery, robotics, and IoT-enabled drones. The integration of these components facilitates real-time data collection and autonomous decision-making in agricultural operations. Artificial intelligence and ML, which automate intelligent behavior, benefits stakeholders in precision agriculture and the environment in a variety of as stipulated.

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REFERENCES

Fountas, S., Espejo-Garcia, B., Kasimati, A., Mylonas, N., & Darra, N. (2020). The future of digital agriculture: technologies and opportunities. *IT professional*, **22**(1), 24-28.

Oza, S. R., Panigrahy, S., & Parihar, J. S. (2008). Concurrent use of active and passive microwave remote sensing data for monitoring of rice crop. *International Journal of Applied Earth Observation and Geoinformation*, **10**(3), 296-304.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, **18**(8), 2674.

Mustafa, M., Abbas, A., Bsoul, Q., & Shabbir, A. (2021). Smart Irrigation System Based on the Internet of Things and the Cloud. *Int. J. Mod. Trends Sci. Technol*, **7**(9), 19-24.

Madhumathi, R., Arumuganathan, T., & Shruthi, R. (2022). Internet of things in precision agriculture: A survey on sensing mechanisms, potential applications, and challenges. *Intelligent Sustainable Systems: Proceedings of ICISS* **2021**, 539-553.

Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2020). Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access*, **9**, 4843-4873.

Khriji, S., El Houssaini, D., Kammoun, I., & Kanoun, O. (2021). Precision irrigation: an IoT-enabled wireless sensor network for smart irrigation systems. In *Women in Precision Agriculture* (pp. 107-129). Springer, Cham.

Hou, J. L., Hou, R., Gao, D. S., & Shu, H. R. (2012). The design and implementation of orchard long-distance intelligent irrigation system based on Zigbee and GPRS. *Advanced Materials Research*, **588**, 1593-1597.

García, L., Parra, L., Jimenez, J. M., Lloret, J., & Lorenz, P. (2020). IoT-based smart irrigation systems: An overview on the recent trends on sensors and IoT systems for irrigation in precision agriculture. *Sensors*, **20**(4), 1042.

Li, H., Guo, Y., Zhao, H., Wang, Y., & Chow, D. (2021). Towards automated greenhouse: A state of the art review on greenhouse monitoring methods and technologies based on internet of things. *Computers and Electronics in Agriculture*, **191**, 106558.

Hwang, J., Shin, C., & Yoe, H. (2010). Study on an agricultural environment monitoring server system using wireless sensor networks. *Sensors*, **10**(12), 11189-11211.

Akhter, R., & Sofi, S. A. (2021). Precision agriculture using IoT data analytics and machine learning. *Journal of King Saud University-Computer and Information Sciences*.

Kumar, A., & Hancke, G. P. (2014). A zigbee-based animal health monitoring system. *IEEE Sensors Journal*, **15**(1), 610-617.

Singh, S., Alam, P., Kumar, P., & Kaur, S. (2019, November). Internet of Things for Precision Agriculture Applications. In *2019 Fifth International Conference on Image Information Processing (ICIIP)* (pp. 420-424), IEEE.

Vrchota, J., Pech, M., & Švepešová, I. (2022). Precision Agriculture Technologies for Crop and Livestock Production in the Czech Republic. *Agriculture*, **12**(8), 1080.

Sinwar, D., Dhaka, V. S., Sharma, M. K., & Rani, G. (2020). AI-based yield prediction and smart irrigation. *Internet of Things and Analytics for Agriculture*, **2**, 155-180.

Aggarwal, N., & Singh, D. (2021). Technology assisted farming: Implications of IoT and AI. In *IOP Conference Series: Materials Science and Engineering*, **1022**(1), 012080. IOP Publishing.

Lu, J., Lee, W. S., Gan, H., & Hu, X. (2018). Immature citrus fruit detection based on local binary pattern feature and hierarchical contour analysis. *Biosystems Engineering*, **171**, 78-90.

Ali, I., Cawkwell, F., Dwyer, E., & Green, S. (2016). Modeling managed grassland biomass estimation by using multitemporal remote sensing data—A machine learning approach. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **10**(7), 3254-3264.

Ramos, P. J., Prieto, F. A., Montoya, E. C., & Oliveros, C. E. (2017). Automatic fruit count on coffee branches using computer vision. *Computers and Electronics in Agriculture*, **137**, 9-22.

Sengupta, S., & Lee, W. S. (2014). Identification and determination of the number of immature green citrus fruit in a canopy under different ambient light conditions. *Biosystems Engineering*, **117**, 51-61.

Scurlock, J. M., Johnson, K., & Olson, R. J. (2002). Estimating net primary productivity from grassland biomass dynamics measurements. *Global Change Biology*, **8**(8), 736-753.

Senthilnath, J., Dokania, A., Kandukuri, M., Ramesh, K. N., Anand, G., & Omkar, S. N. (2016). Detection of tomatoes using spectral-spatial methods in remotely sensed RGB images captured by UAV. *Biosystems Engineering*, **146**, 16-32.

Truong, T., Dinh, A., & Wahid, K. (2017, April). An IoT environmental data collection system for fungal detection in crop fields. In *2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)* (pp. 1-4), IEEE.

Ebrahimi, M. A., Khoshtaghaza, M. H., Minaei, S., & Jamshidi, B. (2017). Vision-based pest detection based on SVM classification method. *Computers and Electronics in Agriculture*, **137**, 52-58.

Krishna, M., Sulthana, S. F., Sireesha, V., Prasanna, Y., & Sucharitha, V. (2019). Plant disease detection and pesticide spraying using dip and IoT. *J. Emerg. Technol. Innov. Res*, **6**, 54-58.

Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J., & Hughes, D. P. (2017). Deep learning for image-based cassava disease detection. *Frontiers in Plant Science*, **8**, 1852.

Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, **161**: 272-279.

Zhu, H., Chu, B., Zhang, C., Liu, F., Jiang, L., & He, Y. (2017). Hyperspectral imaging for presymptomatic detection of tobacco disease with successive projections algorithm and machine-learning classifiers. *Scientific Reports*, **7**(1), 4125.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, **18**(8), 2674.

Pantazi, X. E., Tamouridou, A. A., Alexandridis, T. K., Lagopodi, A. L., Kashefi, J., & Moshou, D. (2017). Evaluation of hierarchical self-organising maps for weed mapping using UAS multispectral imagery. *Computers and Electronics in Agriculture*, **139**, 224-230.

Pantazi, X. E., Moshou, D., & Bravo, C. (2016). Active learning system for weed species recognition based on hyperspectral sensing. *Biosystems Engineering*, **146**, 193-202.

Van Klompenburg, T., Kassahun, A., and Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture*, **177**, 105709.

Ramesh, S., & Vydeki, D. (2020). Recognition and classification of paddy leaf diseases using Optimized Deep Neural network with Jaya algorithm. *Information Processing in Agriculture*, **7**(2), 249-260.

Binch, A., & Fox, C. W. (2017). Controlled comparison of machine vision algorithms for Rumex and Urtica detection in grassland. *Computers and Electronics in Agriculture*, **140**, 123-138.

Zhang, M., Li, C., & Yang, F. (2017). Classification of foreign matter embedded inside cotton lint using short wave infrared (SWIR) hyperspectral transmittance imaging. *Computers and Electronics in Agriculture*, **139**, 75-90.

Hu, H., Pan, L., Sun, K., Tu, S., Sun, Y., Wei, Y., & Tu, K. (2017). Differentiation of deciduous-calyx and persistent-calyx pears using hyperspectral reflectance imaging and multivariate analysis. *Computers and Electronics in Agriculture*, **137**, 150-156.

Maione, C., Batista, B. L., Campiglia, A. D., Barbosa Jr, F., & Barbosa, R. M. (2016). Classification of geographic origin of rice by data mining and inductively coupled plasma mass spectrometry. *Computers and Electronics in Agriculture*, **121**, 101-107.

Dutta, R., Smith, D., Rawnsley, R., Bishop-Hurley, G., Hills, J., Timms, G., & Henry, D. (2015). Dynamic cattle behavioural classification using supervised ensemble classifiers. *Computers and Electronics in Agriculture*, **111**, 18-28.

Pegorini, V., Karam, L. Z., Pitta, C. S. R., Cardoso, R., Silva, J. C. C. D., Kalinowski, H. J., ... & Assmann, T. S. (2015). In vivo pattern classification of ingestive behavior in ruminants using FBG sensors and machine learning. *Sensors*, **15**(11), 28456-28471.

Matthews, S. G., Miller, A. L., PlÖtz, T., & Kyriazakis, I. (2017). Automated tracking to measure behavioural changes in pigs for health and welfare monitoring. *Scientific Reports*, **7**(1), 17582.

Yerima, B. P., & Van Ranst, E. (2005). *Introduction to soil science: Soils of the Tropics*. Trafford publishing.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, **18**(8), 2674.

Im, J., Park, S., Park, S., & Rhee, J. (2015, July). AMSR2 Soil moisture downscaling using multisensor products through machine learning approach. *Institute of Electrical and Electronics Engineers Inc*.

Wang, X., Hu, W., Li, K., Song, L., & Song, L. (2018, December). Modeling of soft sensor based on DBN-ELM and its application in measurement of nutrient solution composition for soilless culture. In *2018 IEEE International Conference of Safety Produce Informatization (IICSPI)* (pp. 93-97). IEEE.

Im, J., Park, S., Rhee, J., Baik, J., & Choi, M. (2016). Downscaling of AMSR-E soil moisture with MODIS products using machine learning approaches. *Environmental Earth Sciences*, **75**, 1-19.

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks-based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, *2016*.

Abioye, E. A., Hensel, O., Esau, T. J., Elijah, O., Abidin, M. S. Z., Ayobami, A. S., ... & Nasirahmadi, A. (2022). Precision irrigation management using machine learning and digital farming solutions. *AgriEngineering*, **4**(1), 70-103.

Kamath, R., Balachandra, M., & Prabhu, S. (2019). Raspberry Pi as Visual Sensor Nodes in Precision Agriculture: A Study. *IEEE Access*, **7**(0), 45110-45122.

Kamir, E., Waldner, F., & Hochman, Z. (2020). Estimating wheat yields in Australia using climate records, satellite image time series and machine learning methods. *ISPRS Journal of Photogrammetry and Remote Sensing*, **160**, 124-135.

Beck, P. S., Atzberger, C., Høgda, K. A., Johansen, B., & Skidmore, A. K. (2006). Improved monitoring of vegetation dynamics at very high latitudes: A new method using MODIS NDVI. *Remote Sensing of Environment*, **100**(3), 321-334.

Craninx, M., Fievez, V., Vlaeminck, B., & De Baets, B. (2008). Artificial neural network models of the rumen fermentation pattern in dairy cattle. *Computers and Electronics in Agriculture*, **60**(2), 226-238.

Murugamani, C., Shitharth, S., Hemalatha, S., Kshirsagar, P. R., Riyazuddin, K., Naveed, Q. N., ... & Batu, A. (2022). Machine learning technique for precision agriculture applications in 5G-based internet of things. *Wireless Communications and Mobile Computing*, *2022*.

Al-Hiary, H., Bani-Ahmad, S., Reyalat, M., Braik, M., & Alrahamneh, Z. (2011). Fast and accurate detection and classification of plant diseases. *International Journal of Computer Applications*, **17**(1), 31-38.

Morales, I. R., Cebrián, D. R., Blanco, E. F., & Sierra, A. P. (2016). Early warning in egg production curves from commercial hens: A SVM approach. *Computers and Electronics in Agriculture*, **121**, 169-179.

Nawaz, M., Nazir, T., Javed, A., Masood, M., Rashid, J., Kim, J., & Hussain, A. (2022). A robust deep learning approach for tomato plant leaf disease localization and classification. *Scientific Reports*, **12**(1), 18568.

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