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Research paper

Machine Learning and IoT for Smart Agriculture: A Comprehensive Review

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Abstract

The world's population will grow faster than ever in the next ten years. After this, food will be even more important. The old ways of growing won't be able to feed everyone when they need to. This is why it's important to use cutting-edge technologies to address the issues that arise when there are more people and more food. Smart agriculture heavily relies on AI and IoT for various farming tasks. Smart agriculture serves as the most sustainable approach for modern farms. Farmers use various monitors, including those that measure temperature, water levels, and rainfall. This study explores the potential applications of IoT and machine learning in farming. Another part of this study examines the usefulness and accuracy of various machine learning methods. Machine learning is a valuable tool for predicting the growth of various crops, selecting the most suitable ones for cultivation, and monitoring their progress. These algorithms consider diverse factors such as soil composition and compatibility classification to optimize crop selection for productive and sustainable farming practices.

Keywords: *Smart Agriculture; IoT; Machine Learning; IoT Sensors; Crop yield Prediction.*

1. Introduction

Cultivating crops and rearing animals, commonly referred to as farming, is known as agriculture and plays a vital part in the economics of a nation. [1]. Agriculture produces a substantial amount of food; it is one of the primary social concern areas. [2]. For most of the state's rural population, agriculture remains their main industry and source of income. [3]. The population is growing daily; by 2050, 20.6% of the world's population is predicted to number 9.7 billion. [4]. Farmland loss, natural resource depletion, population growth worldwide, and the unpredictability of environmental conditions have made food security a serious problem for all nations. [5]. Due to a lack of food and a growing population, many countries still experience hunger today. [2]. The main reason behind this issue is the majority of farmers' illiteracy, as they are ignorant of the consequences of climate change, the condition of the soil, and the viability of specific crops, all of which significantly affect crop productivity.[1] [6]. In the past, farmers used to assess soil ripeness by growing plants that would ultimately yield a particular crop. They neglected critical factors such as the water level, temperature, and weather [1]. Currently, these conditions are deteriorating for farms. To ensure that all individuals have an adequate supply of food, additional and superior food must be produced. The situation is crucial due to factors such as the increasing population, the warming climate, and the loss of land [2]. We should employ the resources at our disposal more effectively [6]. There is a higher number of individuals who require sustenance. Agriculture employs this technology alongside other emerging forms of ICT (information and communication technology). Money can be used to cultivate sustenance and maintain the environment. This type of innovation is beneficial for both the business and the environment. It is referred to as "smart agriculture" [7]. "Smart agriculture" is the term used to describe the implementation of new technology on farms to produce a greater quantity and higher quality of food [8]. This improvement is due to the Internet of Things. Farmers can view the weather, temperature, and moisture level of the ground online. The "Internet of Things" [9] comprises a network of interconnected sensors, motors, and other devices. This form of networking enables the transmission and reception of data. The Internet of Things (IoT) enables farmers to establish connections with their properties from any location and at any hour [10].
From crop planting and watering to health and harvesting, smart farming believes that addressing the issues of labor, climate change, and population growth is essential [8]. It enables farmers to determine the precise requirements for water, fertilizer, and herbicides [11]. A representation of the transformative potential of technology in guaranteeing global food security, Figure 1 illustrates the primary idea that inspired the development of the smart farm system. In addition to the crop itself, there is also the soil, water, and chemicals that are required for the crop. These are the primary components that make up the system. When it comes to making a decision, this illustrates that external elements, such as the weather, are also taken into consideration.

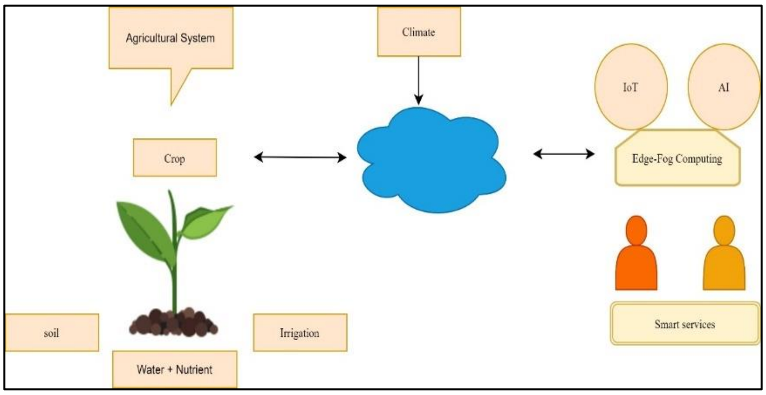

Fig. 1: Illustrates A Framework for an Agricultural System That Utilizes the Different Technologies to Optimize the Crop Management [12].

Table 1: Applications of IoT

IoT Application	Purpose
Soil hydration	Determine the hydration content of the soil to manage irrigation.
Monitoring the Weather	Observe the weather to make well-informed decisions.
Optimizing Yield	Make decisions based on data to maximize yield.
Plant Health	Track plant health to make prompt adjustments.
Remote Observation	For efficiency, remotely observe farm operations.

Table 1 shows IoT Applications in Agriculture and highlights the use of IoT in plant health tracking, yield optimization, weather monitoring, soil hydration determination, and remote farm observation for efficiency.

1.1. Problem statement

Despite farmers in rural areas making substantial financial investments in crop production, they grapple with formidable challenges, including harsh weather, infertile soil, and erratic irrigation, etc. Because these issues make them feel like they are always on the edge, they worry a lot about the future. A lot of farmers are upset that their hard work doesn't seem to be paying off, even though they keep at it.
Objective

- The goal of this paper is to show the people in charge of the farm aid system how to use smart agriculture and machine learning to make choices.
- The goal is to get more people to understand the problems farmers face, such as bad weather, dry land, strange flooding, and more.

This work is made up of five parts. In Part I, explain how important farming is for businesses and countries. It covers resources and articles for crop selection, as well as IoT Applications in water and soil management, or the crucial role that sensors play in this field. This review paper looks into the application of machine learning techniques in agriculture. In IoT-Enabled Smart Agriculture, Section II presents a comparison of machine learning approaches. Section III. wraps up with a review of the literature that covers a wide range of topics. Section IV presents the results, coupled with a thorough examination of the benefits, drawbacks, and prospects for crop management and yield forecasting of machine learning and deep learning techniques. It also includes a detailed analysis of IoT and machine learning applications in smart agriculture. The conclusions and future scope are described in Section V. Section VI of this paper explains abbreviations.

1.2. IoT applications in water and soil management

Through the establishment of automated control systems that maintain a constant watch on land and water resources, Internet of Things technologies enable us to better manage these resources. Sensors that evaluate the condition of the soil monitor its pH, EC, and nutrient levels in order to ensure that fertilizer is used to its full potential. Monitors are used to determine the amount of water that should be used after determining the temperature and moisture level of the soil. It is possible to integrate these approaches into a single system that is beneficial to the environment, saves money, and generates less unwanted waste.
The agricultural industry is transforming with the emergence of the Internet of Things (IoT), causing farmers to have a diverse set of instruments for precise and effective cultivation techniques to overcome field challenges. [1]. In many ways, the Internet of Things (IoT) can help farmers, like it can help them keep an eye on their fields, animals, and small farms [7].
Farmers who want to try new things should use the Internet of Things [13]. This is especially true for farmers who live and work in the country. These apps are important to keep an eye on because they use IoT to send useful info to wireless sensor networks (WSNs). With Wi-Fi cameras and other devices, couples can send and store photos and movies on the grounds and watch them later from afar [14]. Many smart gadgets can access and process data from far away thanks to cloud services [7]. Such technology helps scholars and farmers make better choices. Farmers can check their crops from anywhere in the world if they have a phone that can connect to the Internet of Things. Adding Internet of Things (IoT) technologies could expand the area's capacity [14]. Growing food would reduce costs. Five important ways that ICT is being used to make farming better are shown in Figure 2.
In smart farming, the Internet of Things helps people make better use of water and other resources. [15]. Smart water management monitors, regulates, and makes decisions regarding the quality and quantity of water sources by utilizing various tools and methods. It also involves maintaining the equipment, such as lines and pumps. Numerous tools and apps are capable of interacting with and connecting to water systems. Along with meters, tools for dealing with and showing data, toys, sensors, and more are on this list. [16]. It's not clear how much water plants in domes really need. Using smart devices that can be controlled in various ways through the Internet of Things (IoT) is one way to resolve this issue. These elements are crucial for effective water management. With auto-drip planting, plants can hold water. If there is water on the ground, this method can be changed. This practice keeps water from going to waste by making sure it is used the right way. Many guards always look in the tank to see how much water is there.
After that, the gathered data is kept on the cloud via a mobile app. This technology enables cultivators to keep track of the water level using their smartphones. With the use of this technology, the motor will function automatically. The motor automatically activates when the water's level falls and turns off when the water level rises. Traditional irrigation systems can lose up to 50% of this water due to overwatering

brought on by insufficiencies in methods and practices. IoT-powered smart irrigation systems help farmers solve this problem by reducing water wastage, along with enhancing crop quality through timely watering. On fields, smart irrigation systems install sensors for soil and temperature, which relay field data to cultivators through an information portal. Weather-dependent controllers for precision agriculture keep an eye on local weather data and adjust irrigation schedules accordingly. [14].

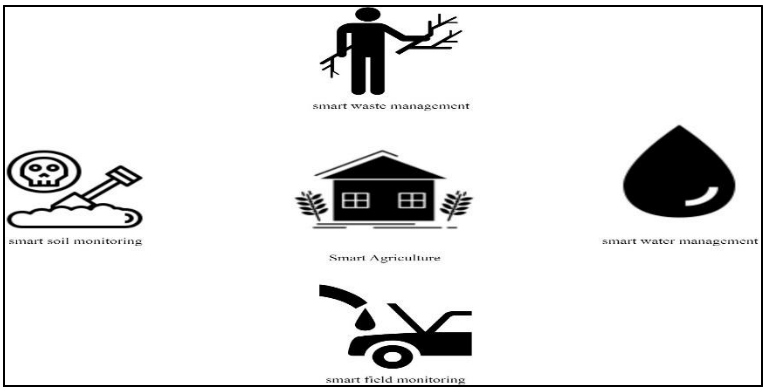

Fig. 2: shows the Smart Agriculture Applications: Waste, Water, Soil, and Field Monitoring.

A wide variety of smart agriculture systems currently available help farmers overcome their everyday challenges. A variety of metrics are gathered by agriculture field monitoring, which farmers can use to take appropriate action to manage planting, watering, harvesting crops, and controlling pests. According to IBM, farmers will be able to boost their yields by 70% by the end of 2050 with the help of smart technologies.

Smart technologies can help farmers with a lot of their everyday challenges in one way or another. [17]. The Internet of Things (IoT) enables various applications such as irrigation decision support, crop growth monitoring, and selection. To modernize and enhance crop productivity, an IoT system utilizing a Raspberry Pi is employed for automatic irrigation. The current scenario sees farmers spending considerable time in the fields to ensure water availability to plants. An irrigation system for precision agriculture is designed with minimally complex circuitry. To provide the system with calibrated data, two sensors—the temperature and soil moisture—are effectively used in the circuit. There are three nodes. Each one has two sensors and a Raspberry Pi processor that can talk to and work with other nodes. All the tests and results indicate that the suggested way solves all the problems that arise when working in the field and adding water. Putting it to use in the field will help things grow faster and better. In this way, the fully controlled watering system also helps people make beneficial choices [18]. It provides farmers with real-time information about their fields and crops.

Ensure that the land is maintained during the farming process. It is crucial to be aware of the dirt's pH level and moisture content. Despite its significance, soil tracking was a difficult task for businesses and farms in the past. People are even more concerned about the environment due to the difficulty of testing the soil. This has a detrimental impact on the food supply. I am more capable of resolving these issues now that I have access to new instruments. Watering, cultivating, and draining farms are effortless. Additionally, the optimal plant variety may be determined by the level of land maintenance. The examination indicates which regions of the soil require fertilizer. When it is necessary to proceed rapidly, a network with minimal latency is necessary. The outcome serves as evidence of the significance of real-time monitoring. In order to acquire a comprehensive understanding of the changes and trends in the agricultural sector, it is crucial to precisely identify these factors. The weather, the amount of rainfall, the fertilizer used, and the condition of the soil are all recorded. This process facilitates our comprehension of the Earth. The moisture content of the land is monitored using checkers that measure flow and humidity. It is imperative that farmers are aware of soil tests, as they are instrumental in the cultivation of superior crops. It is crucial, secure, and advantageous to maintain the land when farming. The practice is now feasible as a result of meticulous testing and the implementation of new technology. In this manner, the vegetation in the yard will not be destroyed by an excessive amount of manure. Smart technology can also be employed to locate muddy terrain. Eliminating grime should preserve and enhance the utility of an object. There is an increase in the production of more commodities, and the quality of cultivation is improved. It is less expensive to acquire items. Ensure that the soil is suitable for the plants before placing them in it. These measures will facilitate the rapid and healthy growth of their roots. The soil necessitates distinct substances for each plant. However, the soil may remain healthy on its own if you conduct research, use organic fertilizer, correct it, protect it with additives, and take other measures [14].

The Internet of Things (IoT) suggests a way to get rid of waste. IoT sensors could imbue cans with intelligence. Through this, one could read, maintain, and distribute data about waste via a network. Waste governance can be accomplished using clever and efficient algorithms. [14].

1.3. IoT sensors

Internet of Things (IoT) sensors are hardware elements that collect information and detect alterations in the surroundings. These are the elements of an ecosystem of the Internet of Things that link both the simulated and reality worlds. IoT sensors are capable of measuring motion, temperature, and pressure. [19]. To track different metrics, sensors might be buried in the ground or positioned at different points around a field. [20]. Additionally, if they are connected to an appropriate network, they can share data with it. [19]. Various sensor types are listed below:

1.3.1. Temperature sensor

Temperature sensors calculate how much heat is produced by a space or an item. Industries such as manufacturing, healthcare, and agriculture use temperature sensors to interpret their findings as data after spotting a temperature shift. Examples of temperature sensors include RTDs (resistor temperature detectors), thermistors, and thermocouples. [19].

1.3.2. Humidity sensor

Humidity sensors are commonly used in many different contexts, including weather monitoring, prediction, and HVAC (heating, ventilation, and air conditioning) systems. These are indispensable instruments for ascertaining the quantity of water vapor present in the atmosphere. These are optimal for museums, hospitals, and parks [19] due to their ability to maintain an exceptionally arid atmosphere.

1.3.3. Soil Moisture Sensor

The quantity of water on Earth can be quantified [9]. When individuals press an object into the earth, they employ measuring instruments to estimate the volume of water it will contain [21]. To ascertain the degree of moisture in an object, carry out the following procedure.

1.3.4. Water level sensor

Water level buoy sensors, also referred to as "drift balls," are cylindrical devices that float on water and other liquids and are equipped with a spot or components that correspond to the specific liquid [9]. It evaluates the quantity of water to determine whether it is excessively high or excessively low. Touching a container is one method of determining its liquid content. Additionally, one was prohibited from interacting with it. It monitors the quantity of a liquid and maintains a record of it [22].

1.3.5. Rain sensor

When it showers on the fields, a set of lights will illuminate. The lamps are capable of distinguishing between rain and water. Utilize this instrument to preserve the health of plants and conserve water. When it showers, the rain sign informs the appropriate individuals. One may also converse with the automobile, irrigate the vegetation, and regulate the lighting in the residence. It is of the utmost importance to ensure the safety of water and prevent its wastage, as it is a necessity for all [23].

1.3.6. Light sensor

Sensors that pick up light and photodetectors are the same thing. They come in many shapes and sizes and are used for many things. In this field, the term "photovoltaic light monitors" is crucial. Picture diodes and picture resistors are some other names for them. One can find out how bright something is, make things work differently when the light changes, and turn it into electricity. They find applications in proximity sensors, automated outdoor lighting systems, light sensing in mobile devices, and renewable energy technologies [24]. It uses light, and different frequencies of light, to quantify the characteristics of the soil. Plant color and soil reflectance data can be obtained and analyzed with the help of these sensors, which can be installed on vehicles or drones. With the use of light sensors, one can determine the amount of clay, organic matter, and soil moisture. [25].

1.3.7. Ultrasonic sensor

Ultrasonic sensors, also referred to as electronic devices, measure a target's distance using ultrasonic sound waves and convert them into electrical signals. [26]. Ultrasonic sensors are useful for many things, such as detecting objects and measuring water and liquid levels. The level of ponds, rivers, and other bodies of water, as well as tanks, silos, and other types of containers, can be measured with great versatility using ultrasonic sensor technology. Moreover, ultrasonic sensors support crop monitoring and fertilizer application. [27].

1.3.8. PIR sensor

PIR sensors, primarily composed of pyroelectric sensors, are capable of measuring infrared radiation levels. They are crucial for tasks or objects that require knowledge of when someone has left or arrived. PIR sensors are ridiculous; they are easy to cross, have a broad glass hearing range, and complicate dominance and essential battle [28]. Highly sensitive to animal motion, a PIR sensor alerts the user when it detects animal entry. Additionally, it triggers a buzzer when it detects motion. [29]. In this article, Table 2 represents the many sensors applied to intelligent farming.

Table 2: IoT Agriculture Utilizes Sensors

Authors & Ref. No	Temperature sensor	Humidity sensor	Soil moisture sensor	Water level sensor	Rain sensor	Light sensor	Ultrasonic sensor	PIR Sensor
Muthunoori Naresh, P Munaswamy [9]	✓	✓	✓	✓				
Tran Anh Khoa et al. [15]	✓	✓	✓	✓	✓			
Ritika Srivastava et al. [8]			✓	✓				
Aman Jain, Abhay Kumar [30]	✓	✓	✓	✓				
Wale Anjali Devanand et al. [29]	✓	✓	✓				✓	✓
Hamza Benyezza et al. [31]	✓	✓	✓					
Ravi Kant Jain et al. [21]	✓	✓	✓					
Bhavya Gupta et al. [32]	✓	✓				✓		

Lova Raju K, V.Vijayara-ghavan [33]	✓	✓	✓
R.Nageswara Rao et al. [18]	✓		✓

1.4. Machine learning in smart agriculture: enhancing performance evaluation and crop yield prediction

Computers can now learn from data without requiring initial programming due to a field of artificial intelligence known as machine learning. In recent times, machine learning has been more beneficial with the development of big data technologies. The term "big data" refers to large quantities of information that are rapidly gathered from multiple sources. Machine learning relies heavily on the creation of mathematical models to better understand data. [34]. A significant volume of data is needed for machine learning, which is the process of teaching a machine. This information can be categorized into training and test cases for machine learning, with a more specific breakdown into illustrations. Training examples are employed to educate the program, which is then applied to consistently deduce new data. After training, the model undergoes validation using testing cases. There are primarily two types of machine learning approaches: supervised and unsupervised.

Supervised Learning: In supervised learning, a teacher supervises the tasks in a program that facilitates the learning process. Support vector machines, Bayesian networks, decision trees, identification distributions, and k-nearest neighbors are merely a few of the numerous methods that can be employed to perform supervised learning.

Unsupervised Learning: Computers are capable of learning a wide range of topics and identifying trends without human intervention. This is called unsupervised learning. People without a full plan for how to do something tend to discover more secret trends. Machine learning incorporates math and statistics in a way that was previously absent. This procedure is done to raise the chances of the predictions coming true. Independent learning methods come in many forms, including K-means clustering, self-organizing maps, hierarchical clustering, partitional clustering, and more.

A variety of items can be discovered in the old data that is utilized for machine learning. Sulfur, phosphorus, potassium, pH, humidity, wind speed, organic carbon, and sulfur are all present. In this instance, the characteristics may be represented as a truth table, a list, or a number. Machine learning is employed to monitor the health of crops, plant them in the appropriate locations, identify ill plants, and maintain land management. Some of the machine learning methods employed in smart farming are illustrated in Figure 3. Farmers who are intelligent possess a wealth of knowledge regarding the commodities they grow. Temperature, humidity, nitrogen (N) or potassium (K) levels, and moisture are among these. Table 3 illustrates several of the most critical components of clever farming. The following are included: potassium (K), boron, nitrogen (N), and zinc [6].

Table 3: Specifications of the Plants and Their Appearance [35]

Features	Description
Nitrogen	The plant will be able to produce heavier and more grains per panicle with the aid of nitrogen.
Phosphorus	Phosphorus is especially crucial for the early stages of development.
Potassium	helps to carry photosynthates to the sink for synthesis.
Zinc	Facilitates the absorption of nutrients
Boron	Boron facilitates fertilization.
Copper	essential to the growth of reproduction.

Machine learning can be employed to facilitate the operation of smart farms. These methods are categorized into two categories: those that are controlled and those that are not controlled, based on the manner in which they manage input and output. Group machine learning methods are crucial for optimizing predictive modeling due to their integration of numerous distinct models. The utilization of these methods to generate multiple decision trees allows others to select which characteristics to employ, rather than relying on a single trait. To achieve the most accurate prediction, we amalgamate the data from each of these models [6].

A self-learning agricultural program is depicted in Figure 3. It is necessary to acquire data, sanitize it, eliminate features, train the model, and utilize it in order to complete the process.

The Internet of Things enables sensors to determine the temperature, humidity, and odor of a location. The material is subsequently modified to facilitate immediate use. This method may be used to ascertain the state of a crop and to determine the irrigation plan that is thought to be the most efficient.

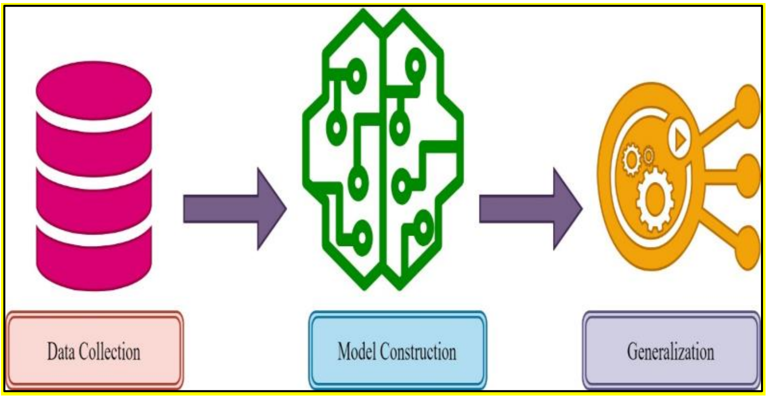

Fig. 3: Illustrates the Comprehensive Methodology for Employing Machine Learning to Analyze Agricultural Data.

Predicting crop yield in agriculture is a key application of machine learning [1]. ML is a crucial tool for supporting decisions in predicting crop yield. It can help with choices about which crops to plant and what to do while the crops are growing [34]. Several methods have been employed to forecast crop yields using various algorithms [3]. Three machine learning models—RF, SVR, and PR—were assessed for their predictive capability in estimating maize and Irish potato yields based on data from Musanze [36]. Agricultural yield (sorghum, peanuts, maize, and millet) is predicted using three widely used machine learning techniques: random forest (RF), neural network (NN), and support vector machine (SVM) [37].

In the context of maize output in the US maize Belt, machine learning is used to enhance estimates. Five machine learning models—XGBoost, Random Forest, LightGBM, LASSO, and linear regression —along with six models of ensembles have been created specifically for this use. [38]. Moreover, to forecast the type and amount of moisture in soil and soil nutrient content, twenty classifiers such as bagging, neural networks, SVM, AdaBoost, and RF are employed. Also, rely heavily on these filters to organize the compounds in the soil into categories. The study also includes a village-specific population measure [39] and levels. Crop prediction analysis utilizes a range of soil parameters, such as pH, phosphate, potassium, sunshine, and humidity. Additionally, atmospheric parameters like humidity, rainfall, and nitrogen are considered in the analysis to forecast the optimal crop for cultivation. It investigates the climate change on rainfed agriculture output. It advocates for early information exchange, especially regarding predicted yield, to enhance planning and potentially reduce food poverty. For instance, the yield of potato (Solanum tuberosum) tubers can be forecasted using proximate sensing data on soil and crop parameters. A quartet of machine learning algorithms —support vector regression (SVR), linear regression (LR), k-nearest neighbor (k-NN), and elastic net (EN)—is utilized for this purpose. [40]. The sources and articles on crop selection are shown in Table 4.

Table 4: Articles and Sources for Crop Selection

Author & Ref. No	Source	Methods	Parameters
Karan and Farhana (2022) [3]	International Journal of Engineering Applied Sciences and Technology	Artificial Neural Network	Temperature, rainfall, humidity, soil nutrients, etc.
Farhat Abbas et al. (2020) [40]	Agronomy (MDPI)	Support vector regression, k-nearest neighbor, Elastic Net, and Linear regression	Soil moisture, soil pH, field slope, etc.
Lontsi Saadio Cedric et al. (2022) [34]	Smart Agricultural Technology (Elsevier)	K-nearest neighbor, decision tree, logistic regression, etc.	Temperature, precipitation, yield, etc.
Martin Kuradusenge et al. (2023) [36]	Agriculture (MDPI)	Random Forest, Polynomial Regression, Support Vector Regressor	Air temperature, rainfall, etc.
Alioune and Benjamin (2022) [37]	International Journal of Climatology	Support Vector Machine(SVM), Random Forest(RF), Neural Network(NN), and Least Absolute Shrinkage and Selection Operator (LASSO)	Temperature, rainfall.
Mohsen Shahhosseini et al. (2021) [38]	Nature (Scientific Reports)	Linear Regression, LASSO, Light GBM, Random Forest, and XGBoost	Air temperature, Soil bulk density, soil pH, etc.
Yan Di et al. (2022) [41]	Agronomy (MDPI)	Support Vector Machine, BO-LSTM, LASSO	Precipitation, Minimum temperature, maximum temperature, etc.

This table includes the numerous studies that have been conducted by different authors along with their reference numbers, sources, methodologies, and other details.

Table 5: Comprehensive Evaluation of Crop Performance with Different Algorithms and Environmental Factors

Author & Ref. No	Crops	Algorithms	Features	Enhanced Performance
Farhat Abbas et al. [40]	potato	LR, EN, k-NN, SVM	soil moisture, soil pH, etc.	SVM
Dilli Paudel et al. [42]	potatoes, sugar beet, sunflower, soft wheat, and spring barley	RR, k-NN, SVR, GBDT	temperature, precipitation, etc.	GBDT
Lontsi Saadio Cedric et al. [34]	bananas, yams, rice, maize, cassava, and seed cotton	DT, MLR, k-NN	precipitation, temperature, pesticide, etc	DT
Martin Kuradusenge et al. [36]	Irish potato, maize	RF, SVR, PR	rainfall, temperature	RF
Yan Di et al. [41]	wheat	BO-LSTM, LASSO, SVM	minimum temperature, maximum temperature, precipitation, etc.	BO-LSTM
Sonal Agarwal and Sandhya Tarar [43]	wheat	RF, DT, ANN(ML) LSTM, RNN, SVM(DL)	rainfall, pH value, relative humidity, temperature	LSTM, RNN, SVM(DL)

This table includes information on the enhanced performance method, crops, reference numbers, and algorithms used, as well as an overview of multiple studies conducted by different authors.

Many studies have been conducted to determine the effectiveness of machine learning in smart farming. Regardless of the circumstances, the efficiency of the system is contingent upon the quantity of data and space that are accessible. However, Support Vector Machines (SVM) necessitate a significant amount of computational capacity, rendering them unsuitable for small farms with limited financial resources [38]. When working with minor quantities, they function exceptionally well. RF models are user-friendly and straightforward to comprehend; however, they are also more adept at managing data loss and noise [41]. To accurately forecast time-series data, such as weather or agricultural growth, deep learning models such as LSTM require a significant amount of named data and a significant amount of computational capacity. This is the reason why the optimal machine learning approach is contingent upon the computer's performance, the scale of the farm, and the quantity of data.

2. Literature Review

The study [44] Explains that the population increase has created issues for the agricultural industry, requiring modernization to satisfy food demands through IoT and machine learning technology for crop output prediction. Relevant research sources estimate that 821 million people worldwide struggle with hunger, and 500 million suffer from malnutrition. [45].

However, in the study [46] Balancing population increase with the increasing demand for food supply poses significant hurdles, which were explained. Machine learning (ML), deep learning (DL), and the Internet of Things (IoT) are among the emerging technologies that have the potential to address these challenges.

This has revolutionized the agricultural industry and brought it into the present day. There are numerous positive aspects to the study [1]. According to the research, precise cultivation can facilitate operations, reduce labor expenses, and increase productivity. Decision trees

and knowledge graphs (KNNs) are two widely recognized methods for predicting the growth of plants. This investigation assesses the efficacy of a variety of machine learning applications. According to a study [47], the three most critical technologies for precise farming are the Internet of Things (IoT), robotics, and artificial intelligence (AI). The fundamental elements of small-scale cultivation are depicted in Figure 4. Some of these components include cloud-based data, contact tools, and surveillance networks. The combination of these components results in a closed-loop system that assists individuals in determining their next course of action.
Farming employs a variety of technologies, including the Internet of Things (IoT), GPS-guided tools, robotics, sensors, drones, and remote tracking. It is possible to optimize resource utilization, increase food production, and ensure that these instruments remain current with advancements in the field [48].

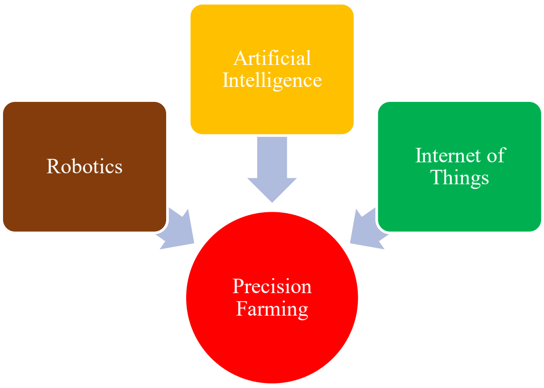

Fig. 4: Depicts The Internet of Things Components Used in A Precision Agricultural System.

Others can accurately predict plant growth, item cost, and the method of eliminating vermin from a farm. By utilizing a diverse array of machine learning tools and methodologies, smart farming achieves each of these objectives. The efficacy of smart farming can be improved through the use of machine learning. It can help producers determine the appropriate quantity of food to cultivate and reduce the likelihood of droughts, among other benefits. The WPART method is the most effective approach for machine learning, according to the study [7]. The F-score, intelligence, accuracy, and agility were among the numerous enhancements. To apply deep learning and machine learning to farming, this paper [6] implements a diverse array of techniques. The development of crops, the selection of consumables, and the land's water and health requirements must be meticulously assessed by farmers. Farmers employ a variety of learning techniques to predict fluctuations in the commodity market, agricultural yields, and costs.
A frequent issue for consideration is the potential of ELMs to facilitate the more rapid and efficient selection of crops than traditional feedforward networks. ELMs are currently undergoing repairs to improve their capacity to precisely predict the presence of compounds in the soil. This is the primary objective of the investigation [49]. Soil is assigned a numerical value that determines its variety based on its pH, phosphorus (P), potassium (K), boron (B), and organic carbon (OC). In order to organize objects, various activation functions are implemented in ELMs. The hyperbolic tangent, the sine-squared, the triangle base, and the wide spectrum of radii are all examples of these. Object categorization presents five obstacles. Even though they are all distinct, the Gaussian radial basis function is more effective for four of them than for the other two. The hyperbolic tangent activation function is the most effective method for performing the pH classification assignment. In contrast, the Gaussian radial basis function functions satisfactorily. The paper assesses the efficacy of prediction and classification using a diverse array of methodologies. The Ace Score, Kappa, Precision, and F Score are among the numerous examples.
Soil is put into groups in the study [39] based on its pH level and the amounts of boron (B), phosphorus (P), potassium (K), and organic carbon (OC) that are in it. Only 10% of the data is used for training in cross-validation. The other 90% is used for accuracy checks. There are ten steps to this process. Finally, the extreme learning method (ELM) is used to quickly sort the data and find out what vitamins are in the dirt. The methodology is optimized using activation functions such as the Gaussian radial basis, sine-squared, hyperbolic tangent, and hard limit. Gaussian radial basis functions (RBF) are specifically used in the paper. [50] To achieve better performance when applying extreme learning machine (ELM) techniques for soil parameter classification. Predicting soil properties has been studied using models for machine learning (ML), including artificial neural networks (ANN), support vector machines (SVM), least squares SVM (LSSVM), decision trees (DT), random forests (RF), Naive Bayes (NB), and SVM. The amount of nutrients in soil has been estimated using machine learning techniques such as ANN and SVM models. Enhanced soil parameters have been successfully used to predict soil fertility through predictive methods, which decrease human intervention and increase accuracy. Supervised machine learning models (SVM, KNN, DT) have been used to predict soil fertility based on the micro and macro nutrient status. Fertility index predictions have been made using a variety of regression techniques, such as boosting NN, DL, SVM, RF, bagging, Bayesian models, lasso, and ridge regression. The dirt's richness was determined by combining two types of spectroscopy. This initiative has provided us with the ability to predict the success of certain commodities by utilizing the information we have gathered about the land. The investigation [51] examined three primary categories of crops: rice, wheat, and sugarcane. The study's SVM and other machine learning tools significantly rely on kernels and decision trees. It is fascinating that this approach can offer advice on the preparation of soil and the planting of crops for all three crop varieties. The model was accurate 92% of the time if it received a 92% score. Based on your understanding of the crop and the land, that is a reasonable estimate. It is not recommended to employ a linear kernel in an SVM. Instead, contemplate the placement of one or more decision trees in the center. This approach will prove more advantageous. The number may increase even further if the curve is not linear.
The quantity of edible commodities that will be produced in smart farming is predicted using a two-tier hybrid machine-learning method that is enabled by IoT [52]. Classification, feature selection (FS), and preprocessing are the three primary components of the proposed model. Two methods are implemented to ascertain which characteristics should be implemented during the initial processing phase: the Correlation FS (CBFS) and the Variance Inflation Factor (VIF). The machine learning model's initial level instructs us to utilize the Adaptive k-nearest Centroid Neighbour Classifier (aKNCN) to categorize soil samples into groups in accordance with the organization of the input soil. This procedure will aid in the determination of the soil's composition. What is the Extreme Learning Machine (ELM)? In the subsequent phase, it is implemented to ascertain the potential revenue that can be generated through cultivation. A novel method known as mBOA can be employed to modify the weights. This simplifies ELM and improves its functionality. MedAE, MAE, RMSE, R^2, MSE, and MSLE are among the evaluations that are implemented to assess the model's efficacy. This investigation accurately predicted the growth of winter wheat [41]. They employed a Bayesian optimization-based long- and short-term memory model (BO-LSTM) to identify specific

aspects of agricultural growth, compiling data from a variety of sources. Consequently, we were obligated to assess the potential responses of the Lasso operator, the support vector machine (SVM), and the BO-LSTM to a diverse array of input factors. Bayesian optimization was identified as an effective method for hyperparameter optimization in deep learning. The primary objective of this investigation is to forecast the growth of vegetation through the use of artificial neural networks (ANNs) and data [3]. In accordance with the land's temperature, weather, and water availability, the quantity of food produced may fluctuate. In this study, multiple linear regression (MLR) facilitates the straight-line connection between the variables that explain something and the variable that exhibits the outcome. The identification of soil types and the prediction of which plants will thrive in each is another application of the ID3 algorithm and classification. ANN is an exceptional resource for determining the plants that are appropriate for the climate of your region, which includes heat, humidity, and rainfall.

This investigation [53] examines instances that transpire both on land and in the environment. The method is implemented to guarantee that the growth of the organism is optimized. Determining the extent to which business operations influence agricultural predictions requires a significant amount of work. This investigation examines the cost of growth, market prices, average prices, and growth rates from the past. The interconnectedness of various components of the study assures farmers that they are not at risk of receiving an incorrect crop, which could result in a decrease in their yield and financial losses. A farmer can select commodities that are well-suited to their region by considering the weather, the time of year to cultivate, and the type of land they possess. Some of the more challenging stages employed in the support vector machine include Adaboost, Naive Bayes, Support Vector Machine, Bagged Tree, and Artificial Neural Network. These applications are also referred to as "majority voting." This method is more precise and effective, and it can be implemented in any location. They are now able to select the most suitable ingredients for their meals. This research employs deep learning and machine learning [43] to identify the most effective methods for food production. When selecting a crop, it is necessary to consider various factors, including the land, the air, and the weather. There is a procedure known as "machine learning" that the SVM algorithm employs. Both LSTM and RNN use deep learning. 93% accuracy is calculated when using the Random Forest (RF) and Artificial Neural Network (ANN) algorithms. In contrast, the accuracy is determined to be 97% when using the Support Vector Machine (SVM), Recurrent Neural Network (RNN), and Long-Short Term Memory (LSTM) algorithms. Regenerative agricultural methods may be significantly enhanced by AI, ML, and new technologies, which can help improve soil health, boost output, and lessen environmental impact. [54].

In this paper[55] Demonstrated that Internet of Things (IoT) systems that were linked to the edge produced much quicker irrigation. The CNN–LSTM mixed models developed by [56] Make it simpler to identify illnesses in the field by combining data from a variety of locations and periods of time. This is going to demonstrate a fresh approach to farming using artificial intelligence right now. It is risk-free, easy to use, and in real time. Even when the internet is sluggish, they continue to function.

3. Findings

Table 6: A Comprehensive Evaluation of Deep Learning and Machine Learning Methods for Crop Management and Yield Forecasting

Research paper	Approach/ Methodology	Important Findings
Study on Precision Agriculture	For crop prediction, it uses machine learning algorithms like decision trees and support vector machines (SVM). Its main objective is to evaluate the models' accuracy scores. Constructs a comprehensive solution by integrating various technologies and machine learning techniques. Handles difficulties with cost estimation, pest control, and crop forecasting.	Reduces labor expenses and streamlines processes. Increases general productivity. Emphasizes the WPART method's superior performance.
Classification of Soil Nutrients	Uses the Extreme Learning Machine (ELM) to quickly learn categorization. Makes use of different activation functions to optimize ELM. Classifies soil using its features. Recall is used to rate success, Accuracy Score, Precision, Kappa, and F Score.	For the majority of classification problems, the Gaussian radial basis function performs better. For pH classification, the hyperbolic tangent activation function produces the best results.
Forecasting Crop Suitability	It primarily pertains to three varieties of crops: rice, sorghum, and wheat. A decision tree and a kernel can be employed to facilitate SVM vector machine learning. It simultaneously displays minerals and earth energies. A favorable outcome is feasible in 92% of cases. It is stated that the most effective method is to employ SVM with a linear kernel.	SVM with a linear kernel works better than other algorithms. Capability to forecast the best crop based on input parameters and soil characteristics
Hybrid Machine Learning with IoT Capability for Yield Prediction	It suggests a two-tiered strategy that includes feature selection, classification, and pre-processing. Extreme Learning Machine and Adaptive k-nearest Centroid Neighbour Classifier (aKNCN) algorithms are employed. For weight updates, the modified Butterfly Optimization Algorithm (mBOA) is used. Uses a variety of metrics to evaluate the model.	Exhibits accurate forecasting of crop yield and assessment of soil quality. Uses cutting-edge optimization strategies for enhanced performance.
Fusion of Multi-Source Data for Crop Yield Forecasting	The LSTM model-based Bayesian optimization method is a method that is discussed by individuals as a means of identifying characteristics that demonstrate the growth of objects. Evaluate the accuracy of Lasso, SVM, and other models in predicting the return. Different categories of information are employed to fill the voids.	Bayesian optimization makes deep learning hyperparameter optimization efficient.
Crop Yield Prediction Using Soil and Environmental Parameters	Different types of linear regression (MLR) can be employed to illustrate connections. The classification and ID3 method are employed by individuals to attempt to determine the type of soil and the plants that will thrive in it. The weather can be influenced by heat, moisture, and humidity in the following ways.	It demonstrates the usefulness of artificial neural networks (ANN) in predicting crops that will thrive in a given environment.
Appropriate Crop Selection Recommendation System	Analyzes yield datasets, market prices, standard prices, and cultivation costs. Defines relationships between different characteristics to support well-informed choices. Adaboost, SVM, Bagged Tree, Naive Bayes, and ANN are examples of sophisticated algorithms used to integrate an ensemble model. Improves the recommendation system's dependability and accuracy.	Enables farmers to choose the best crops for their needs.
Predicting Ideal Crop Yield Using ML and DL Methodologies	RNN and LSTM are employed to facilitate profound learning. Also employ SVM as a machine learns. It is accurate 97% of the time when using LSTM, RNN, and SVM. Random Forest and ANN are accurate 93% of the time.	Utilizing deep learning and machine learning techniques exhibits a high level of precision in forecasting the optimal crop production.

A significant amount of research has been required to determine the most effective farming methods, dividing soil chemicals into categories, predicting crop compatibility, evaluating productivity, and selecting the most suitable crops. This table provides a concise overview of a significant number of them. In the publications, they provide an explanation of the methods they employed and the primary findings.

Table 7: A Comprehensive Analysis of Machine Learning and IoT Applications in Smart Agriculture: Merits, Demerits, and Prospects for the Future

Authors & Ref. No	Merits	Demerits	Future scope
Farhat Abbas et al. [40]	• Better yield prediction • Well-informed decisions regarding agriculture • Increased production • Increased profitability	• Inconsistency in sample size • Potential bias in the data • Less validity • Inaccuracy in generalization	• Increase the diversity of the sample • Expand the size of the sample • Enhance generalizability • Include more varieties of crops
Dilli Paudel et al. [42]	• Emphasis on modularity and accuracy • Encourages reusability • Scalable methodology • Flexible design for varying crops and countries	• Dependence on unrelated data sources • Predictive feature designs are complex • Uncertainty in the testing of algorithms	• Improve data quality evaluation • Examine various attributes and algorithms. • Investigate the best hyperparameters • Enhance crop yield prediction models
Lontsi Saadio Cedric et al. [34]	• Improved accuracy • Improved decision-making • Analyzing multiple variables • Supporting ecologically friendly agriculture	• Inadequate analysis • Specific socio-economic evaluation • Inadequate holistic perspective	• Increase prediction accuracy by utilizing cutting-edge methods • Investigating ensemble techniques
Martin Kuradusenge et al. [36]	• Accurate predictions of crop yields • Enhanced planning for agriculture • Reduction of the risk of food insecurity	• Variability in data sources • Potentially inconsistent and biased • Reliability concerns	• Improved forecast accuracy • Including more weather-related variables
Yan Di et al. [41]	• Accurate yield predictions • Improved prediction accuracy • Encouraging performance	• Scalability challenges • Insufficient processing specifications • Inadequate evaluation of efficiency	• Improved model BO-LSTM • Scalability enhancements • Forecasting improvements in efficacy
Hamza Benyezza et al. [31]	• Increased yield • Resource optimization • Labor reduction • Environmental sustainability	• Data vulnerability • Security risks • Compliance issues • Privacy concerns	• Enhanced security of data • Automated maintenance of the system • Energy optimization
Sitharthan R et al. [56]	• Improved accuracy of diagnosis • Better handling of crops	• Limited scalability • Limited applicability	• Improved algorithms for machine learning
Anil V.Turukmane et al. [57]	• Increased profitability • Enhanced efficiency • Data analysis in real-time • Utilizing cutting-edge technologies	• Privacy/Security concerns	• Enhanced ethics and governance of data • Improved protocols for privacy
Santosh K.Smmarwar et al. [58]	• Benchmark dataset usage • Better model functionality • Excellent achievement of accuracy	• Inadequate attention to scalability and efficacy in real-time	• Evaluation of actual datasets
T.Blesslin Sheeba et al. [39]	• Enhancing the soil's quality • Utilizing machine learning for soil analysis • Classification of micronutrients	• Lack of clarity in the methodology	• Improving algorithms to boost accuracy
Franklin M.Ribeiro Junior et al. [59]	• Reduced fog data • Effective data handling	• Not appropriate for large datasets	• Scalability assessment in real-world scenarios
Claudia Bruno et al. [11]	• Better identification of gases • Inexpensive use of sensors	• Long-term reliability of sensors	• Evaluation of algorithms in real-world
Aman Jain, Abhay Kumar [30]	• Improved decision-making.	• Inadequate information regarding the execution	• Evaluating the diversity of sensors
Ritika Srivastava et al. [8]	• Time-saving • Resource optimization	• Reliance on the environment	• Enhanced durability in challenging circumstances
Muthunoori Naresh, P Munaswamy [9]	• Cost-effectiveness • Gathering data based on several variables	• Device ambiguity • Technology omission	• Improvements in IoT technologies
Abdennabi, Bouali et al.[60]	• Effective management of water • Monitoring in real time • Employing innovative technologies	• Reliance on technology • Accessibility and Initial cost • Data Security and Privacy Issues • Limited Testing Scope	• Embedded System's expansion • Including extra sensor integration • Resolving the issues of climate change

The table provides an overview of several research studies on smart agriculture with an emphasis on IoT and machine learning technologies.

3.1. Practical challenges in ML–IoT integration

In spite of the substantial progress that has been made, the incorporation of machine learning and the Internet of Things in agricultural practices continues to be a difficult task. In rural locations, where the network infrastructure is not as established as it should be, there are considerable worries over the preservation and security of data [31]. Farms are vulnerable to cyberattacks since the data that is sent by a large number of Internet of Things devices does not use encryption.
Scalability is another issue that has to be addressed because, as the number of Internet of Things networks grows, there will be a corresponding rise in the amount of data created as well as the expenses that are connected with providing support [59]. Complex machine learning models, such as convolutional neural networks (CNNs) and long short-term memory (LSTMs), are not appropriate for low-power peripheral devices since they demand a significant amount of processing resources. The development of lightweight machine learning frameworks, data validation systems that are based on blockchain technology, and edge computing systems that process data locally is an absolute need in order to solve these difficulties. Both the length of time that data is delayed and the level of security it has will be improved as a result of this.

4. Conclusion & Future Scope

This paper discusses the advancements in agriculture due to technology, particularly the significant role played by the Internet of Things (IoT) and machine learning (ML) in enhancing the field. Different machine learning techniques, including decision trees, support vector machines, random forests, artificial neural networks, and ensemble machine learning with stacking, play crucial roles in optimizing agricultural processes. Insightful data for research could be obtained from smart sensors, helping farmers by suggesting the best crops to sow [61]. Numerous instruments are implemented to acquire information. Some of these monitor variables such as humidity, temperature, and water level. Employing these instruments can optimize your farm operations and achieve greater productivity. The Internet of Things (IoT) and machine learning (ML) are an effective combination that enables businesses to optimize their resource utilization and achieve greater accuracy. Innovative waste management, intelligent soil monitoring, and smart water management were a few of the IoT applications that were covered in this study. The majority of authors in this field have opted to combine two or more machine-learning techniques to achieve more favorable outcomes.
The study also delves into crop prediction by reviewing several sources and articles. For researchers interested in exploring different algorithms and seeking inspiration to develop integrated machine-learning models for more efficient crop selection and management, it provides valuable insights. It serves as a helpful resource for those aiming to deepen their understanding of the subject and create a diverse range of integrated machine-learning models.
It is possible that in the future, peripheral computing and fog computing will be used to do local analysis of Internet of Things data. Consequently, these changes would result in a reduced dependency on cloud services. TinyML is a lightweight machine learning model that makes it possible for tiny farms to put intelligent systems on monitors that use insignificant amounts of electricity. Blockchain technology ensures that all data exchanges are both safe and unchangeable, proving its reliability. By educating models without the use of a central computer, shared learning protects the data that is collected from agricultural operations. To build intelligent agricultural solutions that are both sustainable and scalable, it is necessary for crop experts, programmers of the internet of things (IoT), and developers of artificial intelligence (AI) to collaborate.
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5. Abbreviations

In this article, the following abbreviations are utilized.

IoT	Internet of Things
ML	Machine Learning
WSN	Wireless Sensor Network
SVM	Support Vector Machine
LR	Linear Regression
EN	Elastic Net
MLR	Multiple Linear Regression
ELM	Extreme Learning Machine
ANN	Artificial Neural Network
DT	Decision Tree
RF	Random Forest
LSTM	Long-Short Term Memory
RNN	Recurrent Neural Network
LASSO	Least Absolute Shrinkage and Selection Operator
BO-LSTM	Bayesian Optimization-based Long- and Short-Term Memory Model
GBDT	Gradient Boosted Decision Tree

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