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A critical review on hybrid framework for precise farming with application of Machine Learning (ML) and Internet of Things (IoT)

Ravi Ray Chaudhari,* Sanjay Jain, Shashikant Gupta

Department of Computer Science Engineering, ITM University, Gwalior, India.

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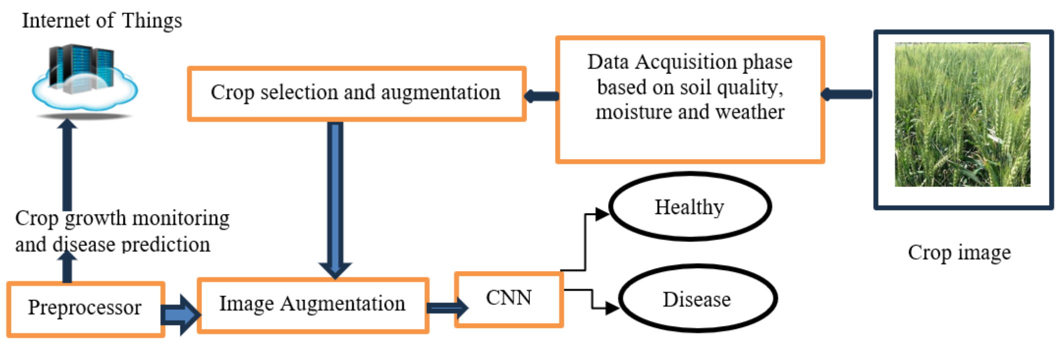
Review

ABSTRACT



Precise Farming, commonly referred to as site-specific crop management, is the use of technology to increase agricultural output and efficiency. Due to the availability of real-time data and insights on crop growth, soil quality, weather patterns, and other crucial elements, the integration of machine learning (ML) and the internet of things (IoT) has completely changed the way farming is done. This review paper focuses on the creation and application of a hybrid IoT and ML system for precise farming. The ML algorithms can process enormous amounts of data and produce insights that can assist farmers in making defensible decisions regarding their farming methods. The framework's IoT devices are in charge of gathering data from diverse sources and transmitting it to a central system for processing. Due to the hybrid nature of the framework, several technologies can be combined to produce a cohesive and effective system for precise farming. By combining ML and IoT, it is possible to use fewer pesticides and fertilizers, increase crop yields, and use less water. The framework is useful for usage in large-scale farming operations due to its adaptability and scalability. In conclusion, the hybrid framework for precise farming that applies ML and IoT is a promising technology that can aid farmers in increasing their output and efficiency while lessening their impact on the environment. Further investigation is required to evaluate its efficacy and identify any implementation difficulties.

Keywords: Precise Farming, Machine Learning, Internet of Things (IoT), Soil Properties, Crop Diseases

INTRODUCTION

Conventional agricultural methods for crop management, which frequently result in resource waste, low yields, and negative environmental effects. The UN estimates that by 2050, there will be 9.7 billion people in the world, or around 2 billion more mouths to feed than there were in 2020. FAO, the UN agency for food and agriculture, estimates that an increase in agricultural production of 70% is required to meet this growth.[1,2] Not to mention that the food business is currently accountable for 22% of greenhouse gas emissions and 30% of the world's energy usage. So, the difficulty lies not simply in increasing food production but also in doing it sustainably. To meet the growing need for food while reducing agriculture's impact on the environment, it is urgently necessary to create more sustainable and effective farming techniques.[3] Precise Farming, usually referred to as site-specific crop management, has emerged as a possible response to these issues. By adapting farming procedures to the unique requirements of each field or even each plant individually, this method seeks to maximize crop development and decrease waste.[4] Precise Farming enables farmers to modify their irrigation, fertilization, and pest control tactics to maximize crop yield while utilizing the fewest number of resources possible. Farmers require access to real-time data regarding the state of their fields and crops to achieve this degree of precision. Here is where the Internet of Things (IoT) and machine learning (ML) technologies must be integrated. The branch of computer science known as machine learning (ML) allows computers to learn without explicitly programmed.[1] The idea of learning machines was

*Corresponding Author: Ravi Ray Chaudhari
Email: raviray.cse@itmuniversity.ac.in

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put forth by Alan Turing in 1950. An artificial intelligence (AI) system provides a framework for forecasting the future or making wise decisions by learning from data and extracting knowledge from it. Figure 1 illustrates the three main components of the machine learning (ML) process: data input, model creation, and generalization. The process of anticipating the outcome for inputs that the algorithm has not yet been trained on is known as generalization. The main applications of machine learning (ML) algorithms include the detection of plant diseases, spam filtering, weather prediction, and pattern recognition.

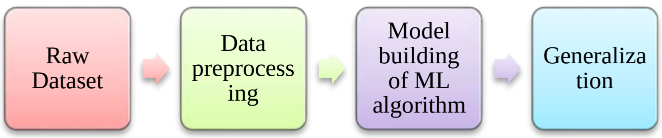

Figure 1. Basic ML Components

In order to help farmers make educated decisions and improve their operations, the integration of ML and IoT can deliver precise and fast information about the state of the soil, weather patterns, and crop growth. Smart sensors that can measure everything from solar radiation to leaf moisture and stem diameter, crop stroage sensing[5] or the temperature of each animal in the case of cattle, enable the Internet of Things to optimize farm monitoring and make a variety of management decisions easier.[6,7] The application of ML and IoT in a hybrid framework for precise farming is a promising technology that has the potential to completely transform the way that farming is done. To produce insights on crop growth and yield, discover anomalies in soil quality, and determine the best times for planting and harvesting, this framework combines the power of data analytics, machine learning algorithms, and IoT sensors. The framework can be used in both small- and large-scale farming operations due to its scalability and adaptability.

Therefore, this paper investigated the creation and deployment of the hybrid framework for precise farming with the use of ML and IoT. We will discuss the different components used in Precise Farming, the benefits of using ML and IoT in agriculture, soil properties, crop selection and disease prediction using ML in Precise Farming and the challenges and opportunities for further research and implementation. We intend to contribute to the ongoing efforts to create more sustainable and effective farming practices by reviewing the state of the technology now and finding potential areas for improvement.

PRECISE FARMING

Precise Farming, also referred to as precision agriculture, is a method of farming that makes use of technology and data analysis to increase the productivity and efficacy of agricultural techniques. It uses a variety of tools, including sensors, drones, GPS, and data analytics, to optimize agricultural inputs and boost crop yields while cutting costs.[8] The fundamental concept behind Precise Farming is to collect data on the variability present in a field, including elements like soil type, moisture content, and nutrient content, and then utilize that data to influence decisions regarding crop planting, fertilization, irrigation, and harvesting. Instead of using uniform treatments throughout the entire field, farmers can adjust their management procedures to meet the unique requirements of each area of the field by doing this. For instance, a farmer can apply fertilizer only to that segment of a field rather than the entire field if they are aware that a certain area of the field has lower soil nutrient levels than the rest of the field. While still ensuring that the crops receive the nutrients they require for their best growth, this can assist to reduce the overall quantity of fertilizer used.[9]

By using less fertilizer, water, and other inputs, as well as lowering soil erosion and other types of land degradation, Precise Farming can also assist farmers in reducing their environmental effect. Precise Farming is a method that aims to maximize agricultural operations via the use of cutting-edge technology and data analysis, with the objectives of boosting productivity, cutting expenses, and enhancing crop yields while minimizing the environmental impact of farming.[10,11]

TOOLS USED IN PRECISE FARMING

Precise Farming involves the use of a wide range of tools and technologies to gather data about the variability within a field and to optimize agricultural practices.[12,13] Some of the key tools used in Precise Farming is shown in figure 2.

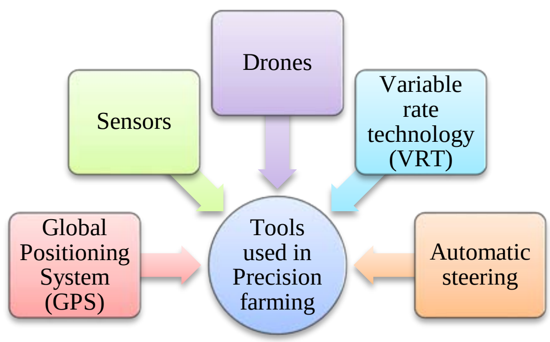

Figure 2. Tools Used in Precise Farming

GPS is a most commonly used tool which is a satellite-based navigation system that may be used to precisely locate and track agricultural machinery in the field, such as tractors and sprayers. Farmers may be able to use inputs like fertilizer and insecticides more precisely as a result of this. Another tool is GIS, With GIS, which is a piece of software, farmers may make precise maps of their fields that include details about the terrain, soil kinds, and other aspects. This can assist farmers in making more educated choices about where to plant, how to fertilize, and how to irrigate their crops. Sensors can also be used to gather information on a range of variables, such as soil moisture, temperature, and nutrient levels, that can have an impact on crop growth. Real-time adjustments to agricultural inputs, such as irrigation and fertilizer applications, can be made using this information.

Another advance tool which is in trend nowadays is drones. That used to gather precise maps of crop health and variability by capturing high-resolution aerial imagery of fields. This data can be used to improve agricultural techniques, such as locating regions that need more irrigation or fertilizer. VRT devices can be utilized to evenly distribute inputs like fertilizers and pesticides. Instead of using standard treatments throughout the entire field, this enables farmers to customize their management approaches to the unique requirements of each area of the field. Last tool is Automatic steering, with the help of automated steering systems, agricultural machinery like tractors and sprayers may be maneuvered precisely in the field. This can aid in reducing input overlaps and skips, which can lead to more effectively using resources.

Techniques Used in Precise Farming

Precise Farming involves several stages, which are often iterative and can be customized to meet the specific needs of a particular farm or crop as shown in figure 3. The first stage of precise farming is to plan and collect data about the farm and the crops to be grown. This involves collect information on soil characteristics, past crop yields, and environmental conditions, as well as mapping the field using resources like GPS and aerial images.[14,15] Second, patterns and trends are found in the data gathered during the planning stage, as well as sections of the field that need various amounts of inputs like fertilizer, water, and pesticides. Making sense of the massive amounts of data gathered requires the use of sophisticated software and statistical analysis tools at this point. Making decisions regarding the best agricultural practices to employ for various fields of work follows the analysis and interpretation stage. This can entail choosing the best crop kinds to use, choosing the best planting density and timing, and producing prescription maps that direct the delivery of inputs. Implementing the agricultural practices chosen during the decision-making stage is the next stage of precise farming.[16,17] In order to maximize efficiency, this may need the use of specialist machinery such variable rate sprayers, seeders, and harvesters. The farm is closely watched after the agricultural methods are put in place to make sure the intended results are being realized. This entails gathering information about yield and other performance measures as well as tracking the growth and health of the crops using sensors and other monitoring equipment. Adjustments can be made to agricultural methods based on this data to improve results immediately. The last step in precise farming is to assess the effectiveness of the agricultural practices being utilized on the farm and adjust for the following growing season. Comparing actual performance to the objectives established during the planning stage and using the learnings to modify the entire process for the following season are the tasks involved in this step.[18]

Overall, precise farming involves several stages, including planning and data collection, analysis and interpretation, decision-making, implementation, monitoring and adjustment, and analysis and evaluation. By optimizing each of these stages, farmers can increase crop yields, reduce costs, and improve environmental sustainability. Precise Farming involves the use of several techniques to optimize agricultural practices and increase crop yields. Here are some of the main techniques used in Precise Farming:

1. Soil sampling and analysis: Precise Farming starts with a thorough understanding of the soil, which is achieved through soil sampling and analysis. This involves taking soil samples from different areas of the field and analyzing them for key parameters such as pH, organic matter content, and nutrient levels. The data obtained from soil analysis can be used to create maps of soil properties and guide the application of fertilizers.
2. Variable rate application: Variable rate application involves applying inputs, such as fertilizers and pesticides, at variable rates across the field, based on the specific needs of each area. This is achieved using tools such as GPS-guided sprayers and spreaders, which can be programmed to vary the application rate according to maps of soil properties.
3. Precision planting: Precision planting involves using equipment such as GPS-guided planters to place seeds at optimal spacing and depth in the field. This can help to improve seedling emergence and reduce plant stress, which can lead to higher yields.
4. Remote sensing: Remote sensing involves the use of technologies such as drones and satellites to collect high-resolution imagery of the field. This data can be used to create maps of crop health, stress, and variability, which can help farmers to identify areas that require additional inputs.
5. Automated steering: Automated steering systems can be used to guide agricultural equipment, such as tractors and sprayers, with a high degree of accuracy. This can help to reduce overlaps and skips in inputs, which can result in more efficient use of resources.
6. Data analytics: Data analytics involves the collection and analysis of large amounts of data, such as yield data, soil data, and weather data, to optimize agricultural practices. This data can be used to create detailed maps of the field, track crop growth, and identify areas that require additional inputs.

Advantages and Disadvantages of Precise Farming

Above conventional farming, Precise Farming has a number of benefits. Precise Farming has a number of benefits over conventional farming methods, such as higher crop yields, lower costs, better resource use efficiency, greater environmental sustainability, better data management, and more effective labor usage. Crop yields may rise because of Precise Farming, which enables farmers to optimize their agricultural techniques.[19] Farmers may make sure that their crops receive the ideal amounts of nutrients and water for growth by adjusting inputs such as water, fertilizer, and pesticides to the unique demands of each region of the field. By using pesticide and fertilizer just where they are needed, Precise Farming can help to save input costs. Farmers may end up saving a lot of money over time because of this. By adapting inputs to the unique requirements of each area of the field, it can also help to reduce waste and maximize the use of resources, like as water and energy. This can lessen farming's negative environmental effects and increase sustainability.[20] By reducing inputs like pesticides and fertilizers that might harm the environment, Precise Farming can assist to lessen the environmental effect of farming. Precise Farming can aid in lowering soil erosion and enhancing soil health by maximizing resource use. Precise Farming involves collecting and analyzing

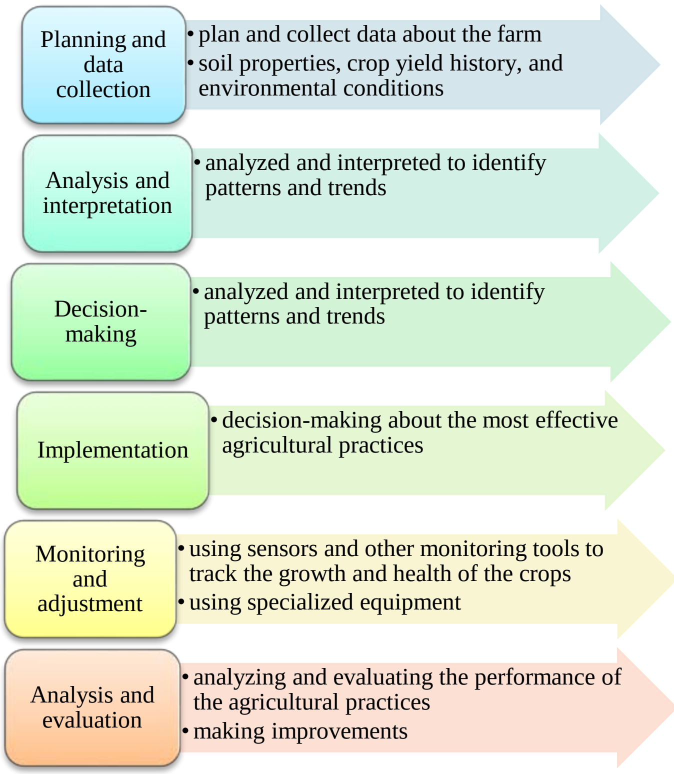

Figure 3. Stages in Precise Farming

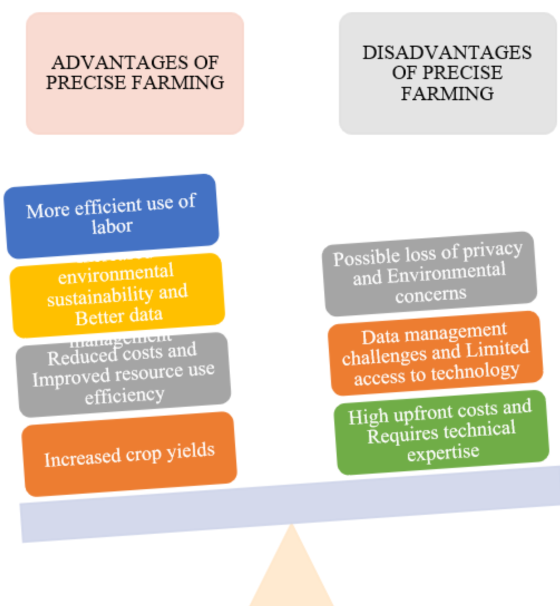

Figure 4. Advantages and Disadvantages of Precise Farming

vast volumes of data, which can assist farmers in making more learned decisions regarding agricultural operations. This information can be used to make precise maps of the field, monitor crop development, and spot regions that need more inputs. By automating some operations, such as the application of inputs and crop growth monitoring, Precise Farming can assist farmers in saving time and effort. This could increase productivity and cut labor expenditures. Some of the advantages and disadvantages are summarized in figure 4.

While Precise Farming offers several benefits, there are also some potential disadvantages to consider while building a framework for precise farming. Precise Farming requires the use of cutting-edge technologies, which might be expensive to adopt, such GPS, sensors, and drones. Some farmers might find it difficult to get started due to the hefty initial investment expenditures. Precise Farming is difficult to install and maintain without a high level of technical expertise. Farmers need to be able to use complicated machinery, interpret maps, and gather and evaluate data. Precise Farming produces a lot of data, which must be carefully handled and evaluated to be valuable. Farmers who are unfamiliar with data analysis methods may find this difficult and may need professional assistance. Some farmers might not have access to the tools required to execute precision agricultural techniques, such as fast internet. Their capacity to gain from these activities may be constrained as a result. Precise Farming entails gathering vast amounts of information about farms and farming methods that may be used by third parties for purposes aside from agricultural efficiency. The usage of some inputs, such as pesticides and fertilizers, can still have severe environmental effects if not utilized properly, even if Precise Farming can help to lessen the environmental impact of farming. Precise Farming has many advantages, but there are also some potential negatives and difficulties to take into account, such as high upfront expenditures, technical competence needs, data administration difficulties, limited access to technology, potential loss of privacy, and environmental issues.

Soil Property Prediction Techniques using ML for Precise Farming

Precise farming includes strategies for predicting soil properties using machine learning (ML). Artificial intelligence known as machine learning enables computers to learn from data and make predictions based on that learning. Here are a few ML algorithms that can be applied to precise farming to forecast soil properties:

1. Regression analysis: Based on input data, regression analysis is a popular machine learning technique for predicting continuous variables, such as soil moisture content. This entails employing a model that has been trained on a dataset of soil samples with known moisture content to forecast the moisture content of new samples.
2. Classification analysis: This ML method may also be used to forecast the characteristics of soil. This involves employing a model that has been trained on a dataset of soil samples with known properties—like soil texture or nutrient content—to forecast the characteristics of new samples.
3. Deep learning: Based on synthetic neural networks, deep learning is a sort of machine learning. This method can be used to predict the properties of new soil samples by first employing a deep neural network to learn from a huge dataset of soil samples with known attributes. For prediction problems including intricate and non-linear interactions

between the input and output variables, deep learning can be especially useful.

4. Support vector machines (SVM): SVM is a technique for machine learning that can be used to predict soil properties. This entails employing a model that has been trained on a dataset of soil samples with known properties to forecast the properties of new samples.
5. Random forest: Random forest is a machine learning technique that is frequently used for soil property prediction. Random forest is particularly useful for prediction tasks that require high-dimensional data, such as soil spectroscopic data. This entails employing a model that has been trained on a dataset of soil samples with known properties to forecast the properties of new samples. Given that it can handle interactions between these input variables, random forest can be very helpful for prediction problems involving numerous input variables.
6. Ismaili et al.[21] developed machine learning approach for identifying soil-suitability maps (SSM) under semi-arid environmental factors. The results show that ML models can accurately predict soil suitability using physicochemical parameters. Shao et al.[22] created machine learning models for maize crop estimation. The model achieved R^2 of 0.69 and RMSE of 0.109. Agyeman et al.[23] tracked the Zn concentration in soil using machine learning algorithms. The model have identified the relation between pretreatment and soil characteristics. Zhao et al.[24] aimed to use machine learning modeling techniques to forecast the presence of heavy metals in rice crops and to identify contributing factors. Goldstein et al.[25] forecasted irrigation suggestions in addition to using the data acquired for crop surveillance and control. The best classification model was the Boosted Tree Classifier, with 95% accuracy, while the best regression model was Gradient Boosted Regression Trees, with 93% accuracy, according to a comparison of the generated models (on the test-set). Using in situ soil sampling, machine learning, and regional satellite-based soil salinity estimates, Shi et al.[26] performed a meta-analysis. For various satellite data under various vegetation conditions, it is also required to choose the proper vegetation and salinity indices. Ding and Du[27] introduced deep reinforcement learning (DRL) for irrigation. To determine the best management strategy, soil moisture content and moisture loss to conserve water from conventional irrigation system. Zhang[28] presented deep learning model to predict vegetation coverages from hyperspectral data. Acharya[29] proposed machine learning algorithm for predicting soil moisture. Chen et al.[30] estimated the soil moisture across winter wheat fields using machine learning techniques. Three cutting-edge machine learning models—support vector regression, random forests (RF), and gradient boosting regression tree—were chosen and contrasted. Below table 1 shows summary of recent technologies for prediction of soil properties using soil parameters using machine learning.

Table 1. Recent Contribution for Soil Property Prediction using Machine Learning

Ref	Year	Methodology	Focused on	Conclusion
[21]	2023	Random Forest, XgbTree, ANN, KNN and SVM	Soil property	AUC is 97%
[22]	2023	SVR and DNN	Soil property	Accuracy is 69% and RMSE is 0.1019
[23]	2023	SVM, Gradient Boosting	Zinc level in soil	R^2 is 13.69, RMSE is 21.08, and MAE is 13.69
[25]	2018	Gradient Boosting Regression Trees	Soil property	Accuracy is 93%
[26]	2022	Bayesian Network	Soil Salinity	R^2 is 0.71
[27]	2022	Deep Reinforcement Learning	Soil moisture	-
[28]	2021	CNN, LSTM	Soil moisture	Accuracy is 91
[30]	2021	SVM, RF, Gradient Boosting	Soil Moisture	RMSE is 2.44.

Challenges and limitations in prediction of soil properties and weather pattern:

1. The universal design of the prediction algorithms has difficulties due to the wide range of geographical situations.
2. The sample selection methodology has a significant impact on the prediction of soil properties.
3. Dataset selection and filtering can be difficult for researchers without a background in computing.

Crop Selection Using ML based on Different Environmental Factors

Crop selection is a crucial step of farming because it can significantly impact the success and sustainability of a farm.[31] Selecting the right crops for a particular location, soil type, and climate can lead to increased yields, reduced input costs, and improved sustainability.[32,33] On the other hand, selecting the wrong crops can lead to lower yields, higher costs, and environmental degradation. Machine learning techniques can be used for crop selection, particularly in different locations or weather conditions.[34] Here are some of the ways that machine learning can be used to select the best crops for a particular location or weather condition:

1. Historical yield data analysis: Machine learning models can be trained on historical yield data for a given location or set of locations. This can allow the model to identify which crops have historically performed well in that location, and which crops have performed poorly. This information can then be used to make predictions about which crops are most likely to perform well in the future.
2. Weather data analysis: Machine learning models can be trained on weather data for a particular location or set of locations. This can allow the model to identify which crops are most likely to perform well under specific weather conditions, such as

temperature, humidity, and precipitation. This information can then be used to recommend the best crops to plant in a given location based on the expected weather conditions.

3. Soil data analysis: Machine learning models can be trained on soil data for a particular location or set of locations. This can allow the model to identify which crops are best suited to the soil conditions in a given location, based on factors such as pH, nutrient content, and soil texture. This information can then be used to recommend the best crops to plant in a given location based on the soil conditions.
4. Crop modeling: Machine learning models can be used to create crop models, which simulate the growth and development of crops under different conditions. These models can be trained on historical yield, weather, and soil data, and can be used to predict the likely performance of different crops under a variety of conditions.

Shetty et al.[35] presented Random forest regression and Multi-Layer Perceptron networks to select crops from soil properties. Su et al.[36] suggested a novel framework for data augmentation. The suggested method, on average, improves the deep neural network's mean intersection over union (IOU) and mean accuracy. raises the average precision and average intersection over union by 94.02% It has also been discussed how the suggested method has some limitations, particularly when there are lots of training data available. Paudel et al.[37] presented machine learning model for crop growth and development to predict crop yield prediction. The Wild Blueberry Pollination Model, a spatially explicit simulation model validated by field observation and experimental data collected in Maine, USA, over the past 30 years, was used by Obsie et al.[38] to generate the data. This study's primary objective is to assess the relative weight of weather variables and bee species composition in controlling wild blueberry agroecosystems. The XGBoost outperformed other algorithms. Han et al.[39] studied the wheat production in regions of China by studying the entire growth period. Yamaç et al.[40] presented machine learning model for prediction of daily crop production. Rezk et al.[41] designed the IoT based precise farming model. Singha et al.[42] developed a machine learning (ML) model using satellite multisensor data, including climatological, SAR backscatter, terrain distribution, and soil factors. Kuradusenge[43] used historical data related with weather and crop yield to predict future crop harvests using machine learning. Sridhara[44] investigated shrinkage regression techniques for pigeon pea yield prediction using long-term weather data. Bhuyan et al.[45] offered a statistical analysis of the features and suggests the best crop type based on the specified features in the context of an Indian smart city. High accuracy was needed when developing a crop forecasting system, and the GB tree technique delivered.

Figure 5 presented the comparative analysis of RMSE of different ML techniques for crop selection. Where it can be concluded the ML based Precise Farming method are more sustainable and better results as compared to other techniques and different ML techniques gives different result based on its advantages and disadvantages. Some general limitations are: the universal design of the forecasting models is complicated by the wide range of factors and the complexity of the datasets. Due to the intricacy, data selection is crucial since it might lead to an underfit or overfit prediction trend.

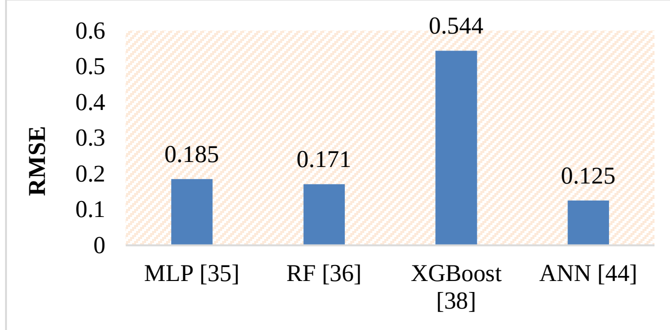

Figure 5. RMSE Analysis of Different ML Techniques for Crop Selection

Crop Disease Prediction for Precise Farming

Crop disease prediction is an important application of machine learning in agriculture. By using machine learning algorithms, farmers can identify potential crop diseases and take preventive measures before the disease spreads and affects the crop yield. Here are some ways in which machine learning can be used for crop disease prediction:

- Image recognition: Machine learning algorithms can be trained on large datasets of images of healthy and diseased crops. These algorithms can then be used to automatically classify new images of crops and detect signs of disease, such as discoloration, wilting, or spotting.
- Sensor data analysis: Farmers can use sensors to collect data on crop health, such as soil moisture, temperature, and humidity. This data can be analyzed using machine learning algorithms to detect patterns and anomalies that may indicate the presence of a crop disease.
- Weather data analysis: Machine learning algorithms can also be used to analyze weather data, such as temperature, precipitation, and wind, to identify weather conditions that are favorable for the development of specific crop diseases.
- Data fusion: Machine learning algorithms can combine data from multiple sources, such as sensor data, weather data, and image data, to provide a more comprehensive picture of crop health and disease risk.

Once a potential crop disease is identified, farmers can take preventive measures, such as adjusting irrigation or fertilizer levels, applying pesticides or fungicides, or removing infected plants. By using machine learning for crop disease prediction, farmers can detect and prevent crop diseases earlier, reducing the risk of crop loss and improving yields. Zhang et al.[49] recommended an improved Faster RCNN to identify four diseases and healthy tomatoes leaves. The enhanced method for agriculture detecting leaf diseases exhibited a quicker detection performance and an identification accuracy that was 2.71% greater than the original Faster RCNN. Iqbal and Talukder[50] suggested an autonomous method that would recognize and categorize potato leaf diseases based on image processing and machine learning. The Random Forest classifier provides an accuracy of 97% for this group. In this way, our suggested strategy leads to a path for automatically detecting plant leaf disease. Lakshmanarao et al.[51] used "Convnets" to detect and categorize plant diseases. From Kaggle, we obtained a PlantViallge dataset. It includes images of 15 different plant leaf classes from the potato, pepper, and tomato families. We split the dataset into three smaller datasets and ran Convnets on each of them. For the detection of tomato, pepper, and potato plant diseases, respectively, we achieved accuracy of 98.3%, 98.5%, and 95%. According to experimental findings, our model has a decent accuracy rate for identifying and classifying plant leaf diseases. Andrianto et al.[52] provided a deep learning-based system for rice disease detection that consists of a smartphone app and a machine learning application running on a cloud server. The train accuracy and test accuracy values for the performance of the VGG16 architecture's rice plant disease detection system are 100% and 60%, respectively. By enhancing the quality of the dataset and expanding the quantity of datasets, the test accuracy value can be raised. Harakannanavar et al.[53] focused on technology that can prevent plant leaf disease. Machine learning techniques like CNN, SVM and KNN, SVM (88%), K-NN (97%) and CNN (99.6%) are used to test the proposed model's accuracy. Sholihati et al.[54] used deep learning such as VGG16 and VGG19 convolutional neural network architectural model. This system enables us to produce an accurate classification system. The experiment's 91% average accuracy demonstrates the viability of the deep neural network strategy. Lijo[55] examined the InceptionV3, DenseNet169, and ResNet50 for image classification and subsequent plant disease diagnosis with and without augmentation. Following the use of the aforementioned strategies, the best model, with an accuracy rate of 97.3 percent without augmentation and 98.2 percent with augmentation. Udutalapally et al.[56] presented the innovative idea of the Internet-of-Agro-Things and describes the automatic identification of plant disease for the construction of ACPS. Most of the products in traditional crops were harmed by microbial diseases. The sample delivered a great efficiency by preventing rust and endure the diverse weather patterns throughout its three months of operation. The accuracy of the suggested crop diseases prediction system is 99.24%. Kumar et al.[57] presented a fungus detection system to construct an expert system for the prediction. More than 98% of predictions for each disease turned out to be accurate on average. This research establishes the viability of employing this method for less expensively and more quickly identifying plant diseases. To identify pests by their eating habits, pest illnesses, and nutritional deficits in coconut plants, Nesarajan et al.[58] created an android mobile application. SVM and CNN were determined to be the best and most suitable classifiers, with accuracy ratings of 93.54% and 93.72%, respectively. The project's results will surely revolutionize the agricultural industry and assist farmers in increasing their production of coconuts. Patle et al.[59] developed a soil moisture sensor (SMS) and leaf wetness sensor (LWS) that are IoT enabled. In order to anticipate plant diseases are employed. Also, we have put into practice the LSTM network, which outperforms the previously mentioned approaches for managing plant diseases. The suggested network yields a 96% accuracy rate, a 97% precision-recall rate, and a 99% F1 score. Below table 2 shows summary of recent technologies for prediction of soil disease using machine learning.

Table 2. Recent Contribution for Crop Disease Prediction using Machine Learning

Ref	Year	Method Used	Type
[49]	2022	Deep Learning-Based k-mean	Crop Leaf
[50]	2020	Random Forest	Early Blight (EB) and Late Blight (LB).
[51]	2021	Deep Learning	Plant leaf disease for pepper, tomato, potato
[52]	2021	VGG16	Rice plants disease prediction
[53]	2022	SVM, KNN AND CNN	Tomato leaves
[54]	2020	VGG16 and VGG19	Potato leaves
[55]	2021	InceptionV3, DenseNet169 and ResNet50	Crop Leaf
[56]	2021	CNN	Microbial Diseases
[58]	2020	SVM AND CNN	Coconut leaves
[59]	2022	LSTM Network	Plant disease

Figure 6 shows the comparative analysis of accuracy of different ML techniques for crop disease detection. Udutalapally et al.[56] method has an maximum accuracy of 99.24%. based on CNN. Method reported by M.A. Iqbal et.al.[50] has an accuracy of 97 %, Deep learning method reported by Lakshmanarao et al.[51] has an accuracy of 98.30 %. Where it can be conclude ML based Precise Farming method are more sustainable and better results as compared to other techniques and different ML techniques gives different result based on its advantages and disadvantages.[60,61]

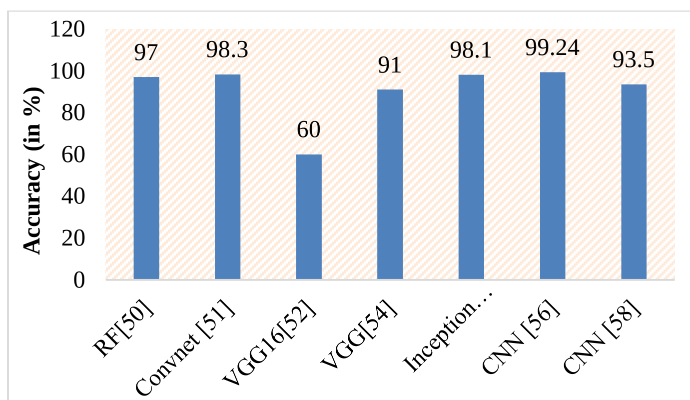

Figure 6. Accuracy Analysis of Different ML Techniques for Crop Disease Detection

Some general limitations are**:**

- The quality of the training data, many of which are accessible as open-source datasets but are relevant to just a small number of crops, determines the accuracy of the prediction.

- As the system's training has a significant impact on how well it performs, incorrectly labeled data might produce a disastrous prediction system.
- The model could become sensitive as a result of overtraining.

Future Work and Current Limitations

There are many areas for future research that could further improve the technology and its influence on agriculture as the field of precise farming with the application of ML and IoT is continually growing. These are a few instances:

1. The creation of new ML algorithms: ML algorithms can always be improved, and academics can work on creating new algorithms that are better suited to quickly processing massive datasets. To increase the precision of predictions, these algorithms can be customized to particular farming scenarios, such as crop types and climate zones.
2. Blockchain technology integration: By integrating with precise farming systems, blockchain technology can offer a safe and open platform for data sharing and crop yield tracking. As a result, farmers may be able to obtain fair pricing for their goods and the supply chain may become more trustworthy and accountable.
3. Usage of drones and robotics: By offering more accurate and effective data gathering and analysis, drones and robotics can complement the use of IoT sensors and ML algorithms. For instance, high-resolution images of crops can be captured by drones and sent to ML algorithms for immediate analysis.
4. The creation of new Internet of Things (IoT) sensors: IoT sensors can be created to deliver more precise and comprehensive data on soil moisture, temperature, and other important variables. Moreover, new sensors can be created to track other aspects of agricultural yield, such as pest infestations and air quality.
5. Extension of precise farming to new crops and regions: Although the technology has already proven successful in a number of crops and places, there is still room to grow it to include additional crops and areas. For a greater variety of crops, researchers can design Precise Farming techniques and verify their efficacy in various climate zones.

Precise Farming with AI and IoT has the potential to completely change the agriculture sector. Nonetheless, there are still several restrictions and areas that require attention in the future:

1. Data accessibility: Accurate farming necessitates easy access to a wealth of high-quality data, such as information on soil moisture, temperature, and weather patterns, as well as information on the health of plants and crops. But in many places, this information is either scarce or nonexistent. Hence, efforts are required to enhance agricultural data gathering and sharing systems.
2. Infrastructure issues: Farmers require access to cutting-edge technologies like IoT sensors and ML algorithms in order to install accurate farming methods. Yet, it may be difficult for farmers to implement these technologies in many areas due to a lack of inexpensive infrastructure.
3. Restricted accessibility and education: Farmers still require training and education in order to use and analyze the data given by IoT sensors and ML algorithms, even if the infrastructure and data are available. To assist farmers in comprehending and utilizing the available technology, there needs to be an increase in the number of training programs and educational opportunities available to them.
4. Integration of various systems: IoT sensors, ML algorithms, and automation tools are just a few of the technology that precise farming systems rely on. Yet, because these technologies are frequently created in isolation, integration can be difficult. Protocol standardization and enhanced interoperability are two areas that require attention.

In conclusion, future work for precise farming utilizing ML and IoT comprises enhancing data availability and infrastructure, boosting accessibility and education, and combining various systems. By overcoming these restrictions and difficulties, precise farming can spread and become more widely available, allowing growers to increase output, cut waste, and create more sustainable and healthy crops.

Conclusion

In conclusion, a viable strategy for changing the agricultural sector is the hybrid framework for precise farming with the integration of ML and IoT. The hybrid framework gives farmers precise, real-time insights about their crops, soil conditions, and other significant aspects affecting agricultural productivity by integrating the power of machine learning algorithms, internet of things devices, and other cutting-edge technologies. The advantages of this technique are obvious: higher sustainability, decreased waste, and better crop yields. Although there are still issues to be resolved, such as data availability, infrastructure restrictions, and the need for more readily available knowledge and training, this technology has the potential to significantly alter agriculture. The hybrid framework for precise farming with the application of ML and IoT can assist to create a more sustainable and productive future for farming, benefiting both farmers and consumers alike, with continuing study, development, and innovation.

Conflict of Interest Statement

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AUTHORS BIOGRAPHIES

Mr. Ravi Ray Chaudhari As a Ph.D Research Scholar ITM University Gwalior. He received his M.Tech from RGPV Bhopal B.Tech from Uttar Pradesh Technological University, Lucknow . His research area includes Artificial Intelligence, Machine Learning and IOT.

Dr. Sanjay Jain is working as a Professor in the Department of Computer Science Engineering, ITM University Gwalior, India. He has awarded M.Tech. and PhD in Computer Science. His research area is Data Analytics, Machine Learning, Deep Learning and Computer Vision. He has guided M.Tech, PhD research scholars in the area of computer vision, image and video processing. He has published number of research papers/articles in reputed Journals and proceedings of Conferences. He has presented papers in various National and Internationals Conferences and Seminars. He has attended and organized various conferences, seminars and faculty development programs at National and International level.

Dr. Shashi Kant Gupta working as Professor in the Department of Computer Science Department, ITM University Gwalior. He received his PhD from NIMS University Jaipur Rajasthan. He did MCA from ITM Gwalior and he completed MTech. From BIST Bhopal. He has a 17 Year Excellence Experience in industry and Education Sector. His research area includes Artificial Intelligence, Machine Learning, IOT and Networking.