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A critical analysis of crop management using Machine Learning towards smart and precise farming

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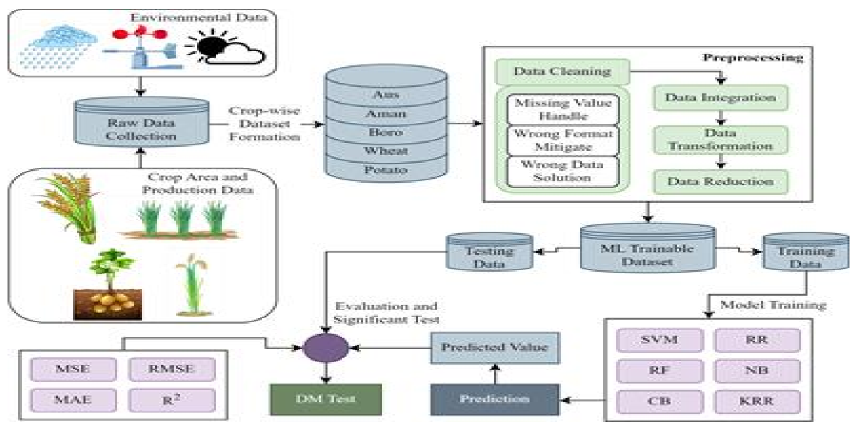
Review

ABSTRACT



Agriculture is one of the key industries that use ground-based and aerial drones for crop health evaluation, crop monitoring, crop spraying, planting, soil and field analysis, irrigation, and other fields. Drones can be flown from a ground station or from the air. The term "precision 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. To put it another way, both plants and animals receive the exact care that they require, which is decided by machines with a precision that exceeds that of a human. Instead of making decisions for an entire field, precision farming enables decisions to be made on a per-square-meter or even per-plant or per-animal basis. This is the primary distinction between traditional farming and precision farming. This article 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.

Keywords: Machine Learning, IOT, Crop selection, Smart Framing, Precise Farming

INTRODUCTION

There have been many revolutions in agriculture, including the domestication of plants and animals a few thousand years ago, the strategic use of farming systems and other advancements in farming practice a few 100 years ago, and the so-called "green revolution" a few decades ago, which included the widespread use of man-made fertilisers and pesticides along with systematic breeding.[1] Based on our findings, we conclude that the tremendous growth of ICT use in agriculture is driving the industry into its fourth revolution. Autonomous and robotic vehicles have been developed for use in farming to carry out duties such as the mechanical removal of weeds, the application of fertiliser, and the harvesting of fruits. Enhanced farm management assistance is possible thanks to the development of autonomous remotely piloted aerial vehicles (RPAVs) and lightweight and powerful hyperspectral snapshot cameras, which can be used to compute biomass development and the fertilisation status of crops. Furthermore, decision-tree models are now widely available, giving farmers the ability to differentiate between different plant problems depending on the info gleaned from the signs manifested in the plant itself.[2,3]

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Cattle herd management is made possible by technology known as virtual fences. These technology advancements, when taken as a whole, represent a technological revolution, which, when combined with other factors, will cause agricultural practises to undergo profound shifts. ICT deployments are being embraced rapidly in both industrialised and developing countries, and have the potential to transform farming in the next decades. These major shifts in the way things are done bring with them not only opportunities but also significant obstacles. It's important to raise these concerns early on in this transformation so that "lock-ins" may be avoided; proponents and detractors of technology should have an honest discussion about how farming will evolve in the digital age. The phrase "smart farming" should only be applied to farming in the digital era.[4]

Farming that is more sustainable leaves less of an impact on the environment. In precision agriculture systems, the application of inputs like fertilisers and pesticides should be minimised or site-specific in order to reduce leaching problems and emissions of greenhouse gases.[5-10] With today's information and communications technology, it is possible to build a sensor network that will enable practically constant monitoring of the farm. The potential of smart farming technology and precision agriculture to satisfy such an ever-growing demand and meet the demands placed on the global food supply are attracting an increasing amount of interest. Increasing crop yields while maintaining or improving the quality of food items is the goal of the smart farming technologies that integrate technology and data-driven agricultural applications. There are several application cases of smart farming currently present all over the world, each of which demonstrates the influence that this new paradigm of agricultural practice is having.[6,7]

However, smart farming encompasses more than just primary crop production. In point of fact, it has had an effect on the entire food supply chain because it uses big data analytics to provide helpful insights about the entire farming process,[10] because it facilitates real-time operational decision-making, and it revolutionizes the business models that are currently used in agriculture. Through the use of on-field smart sensors and gadgets, conventional agricultural methods can be improved using smart farming techniques. These sensors and technologies collaborate with one another in order to make farming more productive while simultaneously enhancing the quality of the crops that are grown.[11]

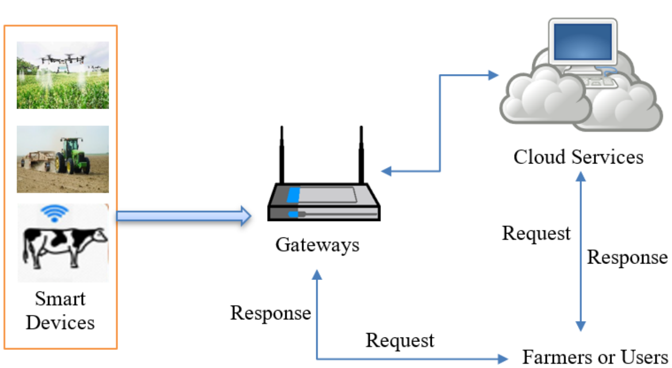

Figure 1. End-to-End Smart Farming Device Communication

The processes involved in farming will become increasingly data-driven and data-enabled as smart technologies and sensors become more prevalent on farms and as the quantity and scope of farm data continue to rise. The phenomenon known as "Smart Farming" is being propelled forward by the rapid development of technologies such as the Internet of Things and cloud computing. Smart farming goes beyond precision agriculture, which merely takes into account in-field variability, by basing managerial functions not only on location but also on data, enhanced by context- and situation-awareness, and triggered by real-time events. Precision agriculture merely takes into account in-field variability.[12,13] In order to carry out agile actions, real-time helping reconfiguration characteristics are essential. This is especially true in the event that the operational conditions or other situations unexpectedly change (e.g. weather or disease alert). These characteristics often involve intelligent aid in the process of putting the technology into use, as well as its maintenance and upkeep.[14]

The concept of "smart farming" can be understood along the management cycle as a cyber-physical system. This indicates that intelligent gadgets that are connected to the internet are the ones in charge of the farm system. Conventional tools, such as rain gauges, tractors, and notebooks, can be upgraded to the level of sophistication attained by smart gadgets by virtue of their autonomous context awareness, built-in intelligence, and ability to either carry out actions on their own or do these actions remotely.[15,16] It is possible to anticipate that the role of humans in analyzing and planning will be increasingly assisted by machines, which will result in the cyber-physical cycle becoming nearly autonomous. Although it is already hinted at in this picture that robots can play an important role in control, it is also possible to anticipate that this will happen. The majority of the operational tasks will be carried out by machines, but humans will continue to be involved in the process in some capacity, although one that requires significantly more intellect.[17-21]

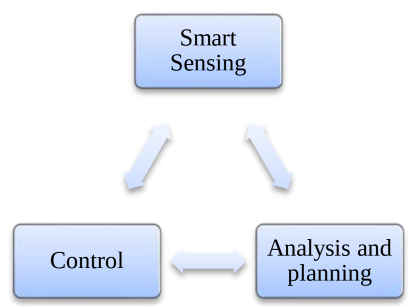

Figure 2. Smart Farming Management Cycle

The term "smart farming" refers to the application of intelligent information and communication technology systems, such as sensors, the internet of things (IoT), artificial intelligence, networking, and cloud-based processes, to the farming system, including livestock farming, aquatic farming, snail farming, and crop cultivation, to name a few.[22,23] It is conceivable to conclude that "smart farming" refers to the use of technological hardware and software solutions to agricultural operations in order to increase farm production. In the past, farmers cleared farmlands in order to prepare them for planting by constructing ditches, employing animals to power the plough, and adopting techniques like bush burning. The traditional farming methods, such as using holes and cutlasses, have given way to more modern methods, such as employing machines to till the fields and machines to harvest the crops. In this regard, the adoption of smart farming techniques has led to the development of a system that is more productive and involves the use of the internet of things (IoT) by farmers to enhance all farming operations and procedures. Using the Internet of Things (IoT) that has been placed on their farms, farmers can now remotely monitor their workers even when they are hundreds of kilometers away from their farms and remotely trigger actuators.

CROP SELECTION FOR PRECISE OR SMART FARMING

There are many varieties of plants, each of which has specific requirements for the kind of soil, the types and amounts of nutrients, and the types and amounts of water. The growing season and the environment of the location in which the plant is cultivated are also factors that influence the amount of water that the plant requires. One is able to maximise harvests and reduce the amount of water that is needed for irrigation if the appropriate crop is grown on the appropriate soil in the appropriate environment [26]. One is able to boost their yields as well as optimise their use of irrigation water and additional fertiliser if they choose the best crop for the conditions that they are growing in. The primary determinants of the water requirements for crops are:

- The climate
- The crop type
- The growth stage

One is able to maximise harvests and reduce the amount of water that is needed for irrigation if the appropriate crop is grown on the appropriate soil in the appropriate environment (Table 1). Reduces the amount of water used for irrigation, hence conserving water resources. Contributes to the preservation of the soil. Farmers are able to increase the effectiveness of insecticides and fertilisers by precisely measuring differences within a field, or they can utilise these products in a selected manner.

Table 1. Example of Water Requirement for Crops

Crop	Crop Water Need (mm/total growing period)
Barley/Oats/Wheat	450-650
Bean	300-500
Cotton	700-1300
Maize	500-800
Rice (paddy)	450-700
Sorghum/Millet	450-650
Soybean	450-700

With the assistance of precision agriculture, Reducing food waste can optimize crop yields by maximizing the amount of food produced. Bhojwani et al.[4] proposed accomplishes this goal is achieved by monitoring the environmental factors—such as temperature, humidity, soil moisture, and so on—that influence the growth of the crop. The approach also helps farmers choose the right kind of idle crop for their needs based on data collection and environmental factors. This approach can be more effective than the conventional methods since it greatly reduces the risk of crop failure, reduced yield, excessive water supply, or excessive use of fertilizers and pesticides, among other issues.

The selection of the most sustainable biomass crop type for use in the manufacture of biofuel presents a multi-criteria decision-making (MCDM) challenge because there are multiple criteria that are in competition with one another. Cobuloglu & Büyüktahtakin[5] offered a novel stochastic analytical hierarchy process (AHP) that is capable of dealing with ambiguous information and determining the relative weights of different criteria in the MCDM problem.

The proposed stochastic AHP approach can also be used to other complex multi-criteria decision-making scenarios involving several stakeholders and possibly include unknown data. By implementing IoT methods, such as a variety of sensors spanning temperature and soil humidity and the use of microcontrollers like Arduino for the processing of Real time data, Patil et al.[6] contributed to a more scientific approach to crop selection. Different sensors and other technological methods were used to achieve this goal. In order to create reliable crop selection predictions, a system will be fed real-time information gathered from a microcontroller, which it will then mine using data mining techniques and compare with predefined trained datasets. The system will be updated with the results of this input. The forecast of the crop will also take into account the prices that are currently being offered on the National Commodity and Derivative Exchange (NCDEX).

Viswanath et al.[7] proposed a prediction method that uses a range of soil and climate characteristics from a dataset specific to the Indian subcontinent to help farmers choose crops. This information is made available to the researchers via the internet. The soil conditions (pH, moisture, etc.) and climate factors (temperature, humidity, etc.) at the preferred location will be analyzed by an Internet of Things (IOT) system. This information is fed into the predictive system, which then determines the type of crop to plant. The developed system can be utilised to achieve healthy crop growth that is adaptable by agricultural practices. This can be accomplished by adopting the system.

Sharififar et al.[9] used square root method, the maximum limitation method, and the fuzzy sets method. In this process the rooting depth, calcium carbonate concentration, organic carbon content, clay content, pH, and slope gradient were the soil properties that were evaluated.

The prediction of the yield is a significant problem and based on the data that is available, it has not yet been solved yet. A brief analysis of crop yield prediction by using data mining techniques based on association rules have been reported for the selected region (a district in Tamil Nadu, India).[10] The results of the experiments show that the proposed work predicts agricultural yields with high accuracy.

A farmer crop selection model was developed by He and Cai[11] in which the model is designed to investigate the maize crop growth. Hepting et al.[12] provided a description of the design and construction of a prototype tool that is intended to assist Canadian farmers in making crop choices. On the other hand, gathering credible information regarding the ideal growth conditions for a crop to achieve its full potential has been challenging. As a result, we propose adding an extension to the prototype system that would enable farmers to submit reports of the performance of their crops combined with data that characterizes the growth conditions in their respective fields. If a significant number of farmers were to provide these experience reports, the data contained within these reports might be mined to offer regionally specific information regarding the productivity of various crops and the environmental factors that are most favorable to each.

An automated crop disease recognition system was proposed by Saeed et al.[13], and it makes use of partial least squares (PLS) regression to choose features from an extracted deep feature set. The outline that has been provided takes into account three key stages. In order for the programme to perform its analysis, the dataset from Plant Village is combed through, and three distinct crops—tomato, corn, and potato—are chosen. When adopting the suggested approach, one can reach an accuracy of roughly 90.1% on average. Not only do the PLS-based fusion and selection methods that have been developed make recognition more accurate, but they also save the amount of time needed for computation.

Phasinam et al.,[14] described a method for tracking and monitoring agricultural production intelligently. These consist of sensors, Internet-of-things connected cameras, mobile applications, and massive data analysis. The hardware consists of an Arduino Uno, several additional sensors, and a Wi-Fi module. We would be able to use energy as efficiently as possible and produce the least amount of waste from agricultural production with this method.

RECOMMENDATION SYSTEMS FOR PRECISE AND SMART FARMING

Crop recommendation is an important area of study in precision agriculture. Multiple factors influence crop suggestions. Site-specific identification of these factors is central to precision agriculture's mission of addressing crop-selection problems.[21] Even if the "site-specific" method has yielded better results, monitoring the outcomes of such systems is still necessary. Inaccurate findings can be produced by some precision agriculture systems. In agriculture, however, it is crucial that advice be given with precision and accuracy to avoid substantial material and capital loss should the advice be incorrect. There are a lot of studies being done to improve the crop forecast model. The general architecture of forecasting model is presented in figure 3.

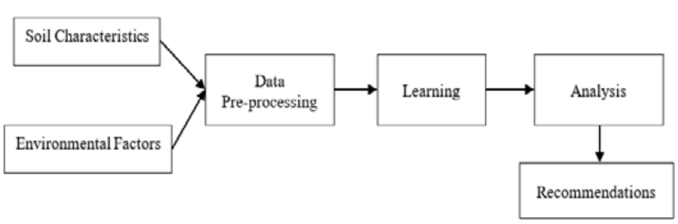

Figure 3. Analysis and Recommendation System for Crop Management

Doshi et al.[23] presented an intelligent system termed as AgroConsultant that provide assistance to farmers regarding crow growth and sowing conditions. The system also provided the recommendation according to soil characteristics and environmental conditions. Mahir et al.[24] proposed a crop recommendation system that analyses the characteristics of the soil in order to make recommendations about the kind of plants that should be grown there. The model for this particular recommender system will take into account the elements such as the soil's moisture content as well as the temperature and humidity. Ahmed et al.[25] proposed nutrient recommendations system for making normal farming in smart farming. For this time series data is processed using genetic algorithm and provided the suitable nutrient requirement of the soil to predict crop yield production. Suresh et al.[26] presented a Harvest Suggestion Framework to aid farmers in determining the quality of the soil. Pawar and Chillarge[27] presented a system that can be of assistance to farmers by raising their awareness regarding the status of their land. Farmers that are knowledgeable about the percentage of nutrients present in the soil can maximise the production of their crops. The nutrients in the soil are impacted when there is toxicity in the soil, which has a knock-on effect on crop health. The proposed technology is able to provide the farmer with information regarding the level of toxicity that is already present in the soil. The dependence of many farmers on rainfall, which is one of the factors that contributes to poor growth and lowers crop production, is problematic. Therefore, the suggested system provides the farmer with recommendations regarding the crop, the fertility of the soil, the level of toxicity, and the supply of water. The precision of the sensor, in addition to the accuracy of the classification algorithm, is particularly critical for this recommendation system. The term "precision agriculture" refers to a modern farming practise that makes use of collected research data on soil features and types, as well as data on crop yields, and then recommends to farmers the type of crop that would provide the highest yield in their particular location. This results in fewer mistakes being made while selecting a crop and a subsequent boost in output. Pudumalar et al.[28] proposed a recommendation system through an ensemble model with majority voting technique that uses CHAID, K-Nearest Neighbor, Naive Bayes and Random tree as learners to recommend a crop for the site-specific parameters with high accuracy and efficiency. Hartono et al.[29] proposed a crop recommendation system based on soil's properties such pH, nitrogen, phosphorus, and potassium. Reddy et al.[30] presented a crop recommendation solutions based on ensemble machine learning approach. This model will provide suitable recommnedation on the basis of soil parameters. Divya et al.[31] used a multi-criteria decision-making (MCDM) tool called fuzzy TOPSIS. This tool is able to function with inputs that are ambiguous and uncertain.

MACHINE LEARNING FOR PRECISE OR SMART FARMING

The process of classifying input data into several specified groups or categories is known as classification. This stage involves actually detecting and categorising input data into different types.[32-36] The real data detection and categorisation occur during this phase, making it the most crucial work in computer vision. Plant images are categorised according to the conditions that have been discovered and then separated into their appropriate groups during this stage of the classification procedure.[37-40] The majority of machine learning strategies can be grouped into one of two types.

Supervised Machine Learning Techniques

The models that will be looked at in this section have been trained to recognise the class label associated with each data item automatically. The data's final label has already been chosen. Listed below are some examples of methods that fall within this category:

Support Vector Machine (SVM): The SVM employs linear criteria in the categorising process and is an option that is appropriate for use in both classification and regression endeavours. An SVM classifier can be thought of as being identical to a single-level decision tree that contains a logically desired multivariate split condition. SVM is made to maximise the distances between the closest data points and the Margin hyper-plane, which ultimately proves to be the correct hyper-plane for decision-making.

Decision Tree: It is simple to comprehend, understand, draw conclusions from, and visualise the method, and it is effective for both numerical and categorical characteristics. It calls for a minimal amount of data pretreatment and eliminates the requirement for hot encoding. It is a model that does not assume any shapes about the data, hence it is known as a non-parametric model. The data does not need to be normalised or scaled, as either of those steps are unnecessary. On the other hand, the Decision Tree is susceptible to overfitting, and even a minor shift in the data can result in a significant shift in the structure of the decision tree, which can lead to instability. When it comes to using regression and making accurate predictions about continuous values, the Decision Tree method falls short.

k-NN: It's a form of learning known as instance based learning, and it's really lazy (IBK). It is common practise to bypass the stage of training model building; instead, one constructs a classification model by directly relating the test instance to the training examples. Using this strategy, a locally optimised model that is tailored to the test case will be created. K-NN is a lazy learning model, which means it does not require any sort of training period. Because of this, it is suitable for seamlessly incorporating new data. It is simple to implement for issues with multiple classes, and it can be used for problems involving classification as well as regression.

Random Forest: It is a group of algorithms known as an ensemble that can efficiently extract useful information from massive datasets. Each tree classifier in this ensemble is responsible for determining the best class for any given sample, and the final class label is arrived at by a voting process that requires a simple majority. Random forest is resistant to the effects of outliers, is effective when working with non-linear data, has a decreased risk of overfitting, and is capable of operating well on a big dataset while maintaining ideal performance margins. These advantages are accompanied by a number of disadvantages, including a lengthy training time, the presence of bias when working with categorical data, and an incompatibility with linear algorithms that contain a significant number of sparse features.

Naïve Bayes Algorithm: The Bayes Classifier, sometimes referred to as the generative model, is the key to unlocking the mystery behind how to calculate the class conditional probability based on the posterior and prior probabilities. The Naive Bayes algorithm is very quick since it operates under the premise that all of the features are independent, and it also performs well with high-dimensional data. Because it is so beneficial, it is also put to use in the resolution of problems involving the prediction of multiple classes. The performance of the Naive Bayes algorithm is outstanding when it comes to categorical values.

Un-Supervised Machine Learning techniques

Unsupervised learning is used when we have unlabelled data. These are categorised in following types:

K-means: K-means clustering is an unsupervised learning approach which have capability of unlabelled problem-solving. Its goal is to group similar items together. It employs a simple process to divide a given data set into several clusters, each of which is designated by the letter "k," the value of which is predetermined. Points are then placed depending on the clusters after that. Work is continued until the desired result is obtained by matching each observation or data point with the collection that encompasses them most closely, calculating and modifying them, and then repeating the technique with the updated modifications.

Fuzzy C-means: Based on the distance amongst each centroids and each data point, this method gives membership to each data point according to that cluster centre. The possibility that the data is a part of the cluster centre increases with the distance between the data and the cluster centre.

Deep Learning

Deep Learning (DL) is a part of machine learning that makes use of ANN. DL makes it easier to create a new feature extractor for every new challenge that arises by simplifying the process. Classifiers based on CNN can be trained on raw images directly, eliminating the need for humans to manually extract features from the images. Recent developments in computer vision, hardware technologies, and deep learning have allowed researchers to improve the accuracy of disease detection as well as other classifications category models. This has enabled them to make more precise predictions. CNN has demonstrated exceptional performance in the fields of automation applicable in any domain such as farming. Below in table 3, the paper presented the contribution of machine learning or deep learning techniques towards precise farming.

Table 3. Machine Learning Contribution in Smart Farming

Ref	Year	Prediction Task	Techniques	Accuracy
[33]	2020	Soil nutrient	Extreme Learning Machine	80%
[34]	2019	Cotton seed variety	CNN	80%
[35]	2021	Disease Detection	CNN	98%
[36]	2018	Apple leaf diseases	AlexNet	91%
[37]	2020	Weed Detection	Random Forest	95%
[38]	2019	Cucumber leaf disease detection	CNN	95%
[39]	2019	Disease Detection	VGG	98%
[40]	2019	Land cover mapping	SVM	84%

CHALLENGES AND FUTURE RESEARCH SCOPE

Data collection, processing, and use for crop yields face a variety of difficulties. Cybersecurity and protecting privacy are two important challenges that farmers must deal with in order to succeed in the digital age. Agricultural technology systems typically have issues with data quality and accessibility. This becomes significantly more challenging when there is more real-time data. Therefore, some of the major concerning areas for smart and precise farming are illustrated in figure 4.

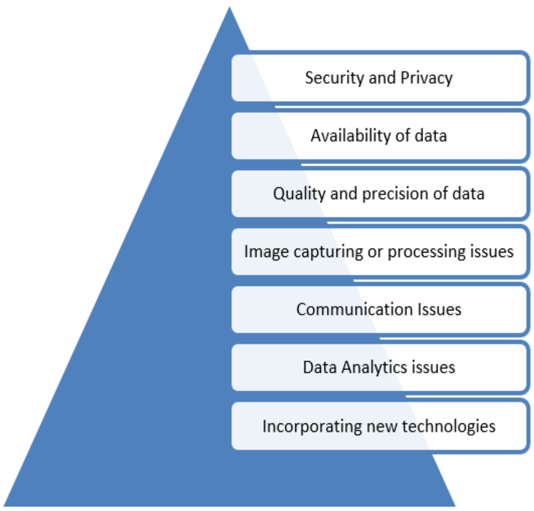

Figure 4. Current Limitations or Challenges in Deployment of Smart and Precise Farming

CONCLUSION

Agriculture is one of the most important industries to include ground-based and aerial drones for a variety of reasons, including but not limited to the evaluation of irrigation, crop monitoring, crop spraying, planting, analysis of soil and fields, and crop health. IoT-based farming solutions that improve farming's accuracy and control fall under the umbrella term of "precision farming," which is also sometimes referred to as "precision agriculture." To put it another way, both plants and animals get the exact care they need, which is determined by machines with an accuracy that exceeds that of a human's. Instead of making decisions on a per-field basis, precision farming allows for them to be made on a per-square-meter, or even per-plant or animal basis. This is the primary difference between conventional farming and precision farming. This article presents an introduction to smart farming, a comprehensive examination of the process of crop selection, and a recommendation system for smart farming.

Among the most crucial industries to use aerial and ground-based drones is implied in agriculture for a number of purposes, such as crop health, soil and field analysis, planting, crop monitoring, crop spraying, irrigation evaluation, and more. Precision farming, also known as precision agriculture, is the general term for IoT-based farming solutions that increase accuracy and control of crop related processes. Stated differently, the precise amount of care required for plants and animals is determined by machines with a level of accuracy that surpasses that of human judgment. Precision farming enables decisions to be made on a per-square-meter, or even per-plant or per-animal basis, as opposed to a per-field basis. This is the main distinction between precision and conventional farming. Smart farming with a thorough analysis of the crop selection procedure, and a smart farming recommendation system have been deliberated with focus on recent advances in the field.

CONFLICT OF INTEREST STATEMENT

Authors do not have conflict of interest.

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