IoT and Machine Learning Approaches for Classification in Smart Farming

Dr. Srinivasa Babu Kasturi[1]
Professor
Department of Computer Science and Engineering
Nalla Narasimha Reddy Education Society's Group of Institutions
Kasturisrinu.babu@gmail.com

CH. Ellaji[2]
Assistant professor,
Department of CSE,
School of Engineering and Technology
Sri Padmavati Mahila visvavidyalayam, Tirupati, AP, India
ellajispmvvcse17@gmail.com

Dr. D. Ganesh[3]
Associate Professor of CSE,
Mohan Babu University
(Erstwhile Sree Vidyanikethan Engineering College (Autonomous),
Tirupati, Andhra Pradesh, India
ganesh.d@vidyanikethan.edu

K. Somasundaram[4]
Professor,
Department of CSE,
Sri Muthukumaran institute of Technology, Mangadu,
Chennai, TN, India
soms72@yahoo.com

B Sreedhar[5]
Assistant professor
Department of CSE
Koneru Lakshamaiah Education Foundation
Guntur
sreedharburada@kluniversity.in

Abstract:

Precision farming is the future of conventional farming. The digitization of farming has led to the development of machine learning (ML) systems in a variety of administrative areas so that more may be gained from the vast quantities of data now available. Knowledge-based farming systems present a number of obstacles, but one area of artificial intelligence with great potential is machine learning & Deep Learning. The development of a number of cutting-edge technologies has made this possible. The idea of this article is to encourage smart farming practices and lessen agricultural risks. While agricultural progress is nothing new, the wireless sensor powered by artificial intelligence will usher in a new era of precision farming. The focus of this study is on developing new machine learning methods for better prediction. Machine learning in agriculture, however, doesn't appear to be in sync with the field's central research. The difficulties already present in agriculture data only serve to exacerbate the situation. The effects of these data problems on several machine learning techniques are also investigated, and applied to the field of agriculture. We have looked at the naive bayes and KNN classification algorithms for precision agriculture in this paper. We have analyzed the data and determined the optimal classification method for use in precision agriculture by taking into account a wide range of factors.

Keywords- Agriculture that is intelligent, Precision agriculture, precision farming, and machine learning.

1. Introduction:

Precision agriculture, often known as digital farming or intelligent agriculture, is the application of technology in farming to increase yields while reducing environmental impact [1-3]. The agricultural sector's reliance on information technology is currently seen as a worry in light of the various challenges that develop in the industry. The use of remote control and environmental monitoring in agriculture is rapidly rising in efficiency and profitability [4]. Both precision farming and "smart farming" have the potential to pave the way in this approach. These two words [5] refer to the use of modern agricultural technology in conjunction with more conventional techniques to increase crop yields. In order to increase productivity and income, farmers can benefit from the information provided by intelligent agriculture systems. Such technological advancements have the potential to improve nearly every facet of agriculture, from plantation & irrigation to plant security and harvesting. Processes become understandable and judgements requiring human involvement are made naturally when AI has been incorporated into the cloud [6-7].Databases and predictive analysis are only two examples of the many methods proposed to address today's problems in agriculture. Artificial intelligence (AI)-based systems have consistently outperformed non-AI counterparts in terms of accuracy and productivity [5]. As a dynamic industry, farming presents unique challenges for which a blanket answer is not possible. By using AI methods, we were capable to efficiently collect data and address each case's specific challenges in light of its own characteristics. As more and more AI systems are developed, even the most intractable issues can be overcome.

Rapid adaptation of various agricultural methods to AI is occurring. By using the idea of smart systems, farmers may identify crops, examine soil, receive guidance from specialists, and create new revenue streams. As a result, stochastic Artificial intelligence technology have developed that enable farming to detect, collect, and respond to changing conditions in order to increase efficiency [8-9]. Farmers who stay abreast of industry developments can provide useful ideas through channels like chatter bots. The use of AI in agriculture is expected to skyrocket worldwide in the coming years [10, 11]. The goal was to increase productivity in farming by implementing technologies including driverless tractors, crop monitoring protocols, computerised irrigation systems, and aerial drones. The purpose of this study was to draw attention to WSN and IoT's usefulness in agriculture and to provide a thorough examination of sensor & IoT data analytics based on AI methods for use in agricultural contexts. The purpose is to discover and manage cotton leaf diseases in order to increase its application in agricultural settings. Figure 1 depicts a common application of IoT and cloud computing in precision agriculture.

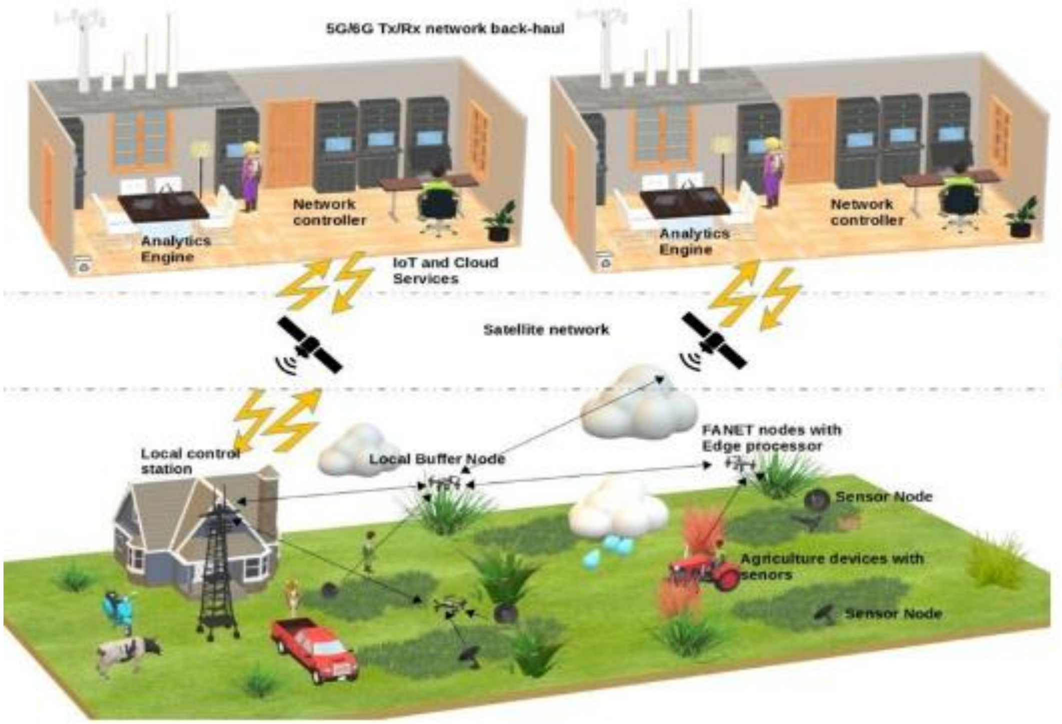

Figure1.Typical Precision Agriculture Ecosystem[32]

Several ideas have been proposed for using ML to aid in agricultural decision-making. In particular, the agriculture, water, and soil industries have received a lot of research and development funding. However, there isn't agreement on how ML techniques should be used among academics. Because agricultural data has some of the most demanding dataset attributes found in the ML field, this is no small problem. To rephrase, many times agricultural data are skewed, sparse, and full of noise [12]-[15]. In the field of disease prediction, for instance, data inconsistencies frequently lead to subpar classification models and, in some cases, inflated estimates of model performance [16, 17]. Furthermore, there is a severe lack of commentary on fundamental factors like the reliability of models. Credibility is crucial for the widespread adoption of ML-driven precision agriculture practises by farmers and for the efficient implementation of these practises by academics. However, little thought appears to have been given to modeling trustworthiness in the ML research within the agricultural sector. In fact, there has been a heightened focus on model accuracy, albeit at times incorrectly.

The remaining paper is organized as follows: Section 2 discusses about extensive literature survey of Precision agriculture and ML techniques used in Agriculture.Section3 discusses about the Proposed Methodology. Section 4 discusses about the dataset used and section5 discusses about the Evaluation and Results and finally section6 concludes the work.

2. Literature Survey:

Several studies have focused on the application of AI, CV, ML, and DL to the field of agriculture. Machine learning can be seen of as a means to an end—namely, the development of AI. Convolution neural networks & recurrent neural networks are examples of deep learning, which is a subfield of machine learning. Some of the above-mentioned words are graphically represented in Fig. 2, which will also be referenced in the next part and throughout this literature review.

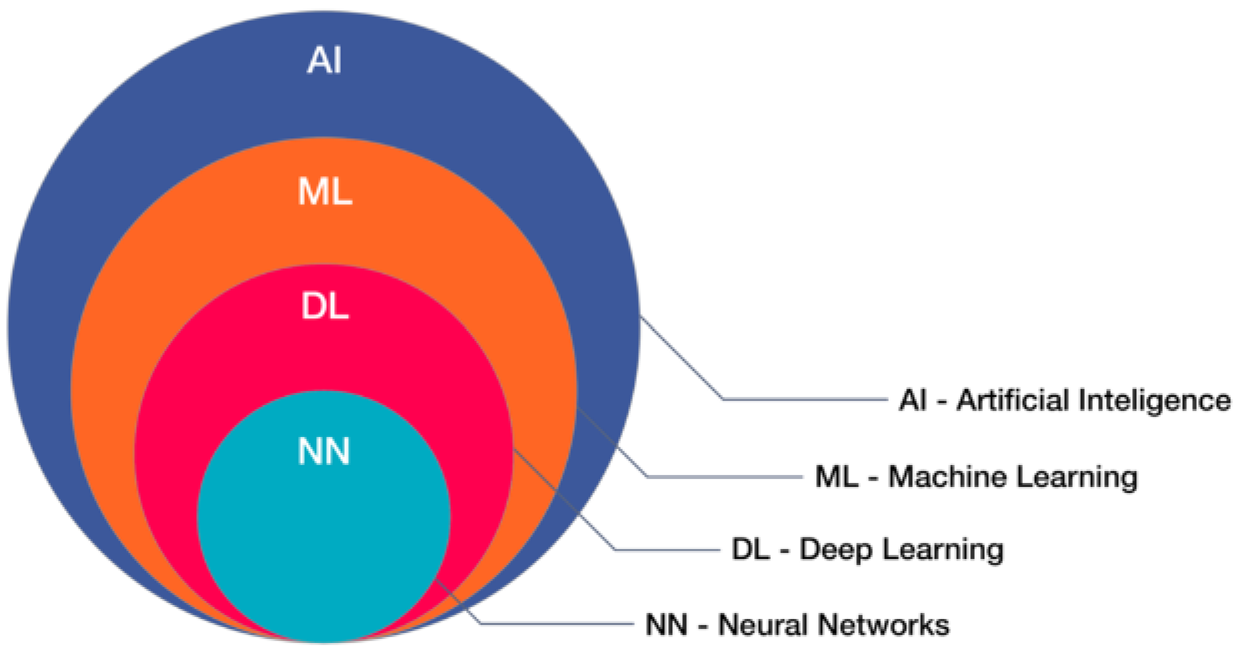

Figure 2.General Relationship between AI, ML & DL

Image and speech recognition, autonomous driving, applications in spam filtering, malware detection, stock market prediction, fluid mechanics, and credit card fraud detection, medical diagnosis, pollution identification in urban water systems, activity recognition, and an abundance of other applications are just some of the many areas where ML is used to aid in management today.

The use of AI in agricultural automation has been reviewed by Jha et al. They looked at available options and came to the conclusion that sensors, IoT, and ML can be utilised to automate agricultural activities [18][42]. Patricio and Rieder examined the use of AI and CV in precision farming. From 2013 to 2017, they looked at 25 studies using only five crops (maize, rice, wheat, soybeans, and barley) and six different databases (Science Direct, Scopus, Springer, Web of Science, ACM, and IEEE). During that time, Support Vector Machine was the most popular choice for classifiers. Cameras were the most common type of input device [19][43]. Tian et al. examined the use of computer vision in farming. Based on their findings, they state, "computer vision technologies combined with artificial intelligence methods will enhance the economic efficiency, general performance, coordination performance, and robust performance of automated agricultural systems." This statement is based on an analysis of 75 publications published between 2015 and 2022. [20]. Paul et al. examined roughly fifty studies (published between 2007 and 2018) with an emphasis on the use of computer vision & machine learning in agricultural settings. And they did saw a big improvement recently [21][41]. Rehman et al. conducted extensive research in this area, reviewing over 200 articles on the topic of machine learning methods for agricultural machine vision systems. They speculated that in the not-too-distant future, "the use of ML technology for weed detection, plant diseases including stress detection, crop forecasting including estimation, water content of plants determination, grading and sorting, soil analysis, and real-time field operations may become routine operation" [22][40].

Forty papers on the application of machine learning to agriculture were analysed by Liakos et al. All of the publications are from peer-reviewed journals, and they were found using Scopus, Science Direct, and Pub Med. They found that ML was discussed in four publications relating to water management, eight papers relating to animal management, and four papers relating to soil management. But majority of the studies (24) are about using ML for managing crops [23][39]. In order to better regulate nitrogen in agriculture, Chlingaryan et al. explored machine learning for predicting crop yields. They also came to the conclusion that the recent decade has seen a dramatic increase in the application of ML and sensing [24]. Sharma et al. also zeroed down on a more specific topic; they utilised machine learning to examine the efficiency of supply chains in sustainable agriculture[44][45][46].

Management of the biological, chemical, and physical components of the crop environment to achieve qualitative as well as quantitative goals is what falls under the umbrella term "crop management" [25][37][38]. Increased production and income result from using cutting-edge methods for Predicting crop profits, diagnosing plant diseases, pulling out unwanted plants, spotting unwanted crops, and evaluating the quality of crops. Precision agriculture aims to improve upon these and other areas.

Predicting agricultural yields is one of the most urgent and difficult issues in the field today. If the model is accurate, farmers can make well-informed decisions about crop allocation in order to better align their manufacturing with the needs of the market [26]. However, it's not a simple endeavour, since it requires a number of actions to be taken. Environment, management, crop genotype and phenotype, and interactions between these all play a role in yield prediction. Therefore, a solid understanding of the link between these interaction factors and output is required. Consequently, complex algorithms like ML methods are required to uncover these types of associations [27][36].

Numerous scientific fields, including as plant taxonomy, botanical gardens, and the discovery of new species, have shown considerable interest in the topic of automatically recognising crops. Leaves, stems, flowers, fruit, roots, & seeds can all be examined to determine a plant's species [28, 29]. The most common approach to plant identification appears to be based on analysing the form, texture, and colour of individual leaves [30]. As more and more farmers turn to satellites and other aerial vehicles to gather data on a wide variety of agricultural qualities, the practise of remotely classifying crops has become increasingly common. Similar to the aforementioned sub-categories, the automatic recognition and classification of crops has benefited from the development of software and processing images devices coupled with ML[32].

Crop quality is heavily influenced by a number of factors, including but not limited to climate and soil conditions, farming practises, and crop features. Farmers should expect higher profits from the sale of higher-quality agricultural products. For instance, in terms of fruit quality, the most common maturity indices used for harvesting are flesh hardness, soluble solids concentration, and skin colour [31]. The date of harvest has a significant impact on the quality features of both crops of great value (tree agricultural products, grapes, herbs, and vegetables, etc.) and agricultural crops. Therefore, improving the quality of agricultural output requires farmers to make informed management decisions, which can be aided by the creation of decision support systems. Selective harvesting is one management technique that has the potential to greatly improve product quality. Additionally, the harvest may be discarded if it does not conform to the specified shape, colour, or volume. making crop quality an additional difficulty that modern agriculture must face. The combination of ML algorithms with image technology can yield promising results, as mentioned above[34][35].

3. Methodology:

Here, we're going to use a set of approaches. The Naive Bayes and K-Nearest Neighbour methods are the first and second, respectively. Using these two strategies, we can achieve precise performance. A java programme is developed to estimate agricultural output. The application process consists of three stages. Data management comes first, followed by data testing, and finally data analysis. By organising datasets, we may get datasets from prior years and transform them into a usable format. Because of the use of the Weka tool, all of the datasets included in this undertaking have been transformed into attribute relation files. In the testing phase, we can conduct tests independently. Two machine learning techniques have been discussed. Naive Bayes and the K-Nearest Neighbour Method are two examples. Any one of several methods can be used to evaluate a dataset, with findings similar those obtained from selecting a single crop, a single location, and a single growing season. In the analysis section, we can load an entire dataset file to compare the two approaches' precision. This aids in foreseeing which approach will prove effective.

The agriculture sector is fraught with difficulties, and we must do what we can to ease the burden on farmers. New farming methods can help alleviate many of these issues. Machine learning techniques can be used in farming. Crops can benefit from our clustering and classification strategies. Some of the techniques used in regression analysis can also be used to raise crop yields. Only the Naive Bayes and K-Nearest Neighbour approaches have been taken into account for this work. By combining these two approaches, we can make educated decisions about which crops to plant where and when. We created a Java app because farmers are unfamiliar with the Weka tool. They can estimate the harvest with the aid of this programme.

Here, we can perform isolated experiments by specifying parameters like crop kind, growing season, and geographical location. Either the KNN or NB technique can be used. As soon as you provide the data, you may choose the analysis technique and begin mining the outcomes. The numbers indicate the crop's potential yield. And by inspecting the data sets, we can conduct many tests. It's useful for analysis because it lets you pick an entire file at once and receive precise results. Here, we may skip the needless repetition of single-testing and get right into the multiple-testing phase. This kind of testing is useful for determining which of two approaches is more precise. This will help us determine which of the available approaches is best. As a result, farmers will have a better idea of what crops to choose for their plots and areas. Previous year's data are included in the datasets. New results for untried instances can be predicted with the aid of these databases. A farmer can test any sample and learn the crop's average production. As a result, this app is useful for helping farmers choose the right crop for their fields. And it helps them estimate how much their chosen crop will produce. These procedures can be carried out manually. In this context, we focus on the values of instances' probabilities. The answer is available for future examples. The likelihood of good and bad outcomes will be calculated using Naive Bayes. In addition, we can forecast whether or not the selected crop will produce a large or small quantities. As with the Least-Squares Neighbour (KNN) method, the minimum value is determined by determining the greatest distance between two instance values. This method uses the Euclidean distance to compare the separation between two numerical values.

The naive bayes classifier is the foundation of the naive bayes algorithm. This classifier aids in determining the likelihood of different classes. Using this strategy, constructing massive datasets is a breeze. Predictive issues in either regression or classification can be tackled with the help of the K-nearest neighbour technique. This methodology is useful for gaining insight from output, determining timing, and increasing forecast accuracy. Machine learning methods have many applications. In the realm of machine learning, KNN is also a viable option. Sample-based learning is another name for this approach. As such, it can be used to make predictions about future datasets based on information from the past. Distance functions, such as the Manhattan distance or the Euclidean distance, will be used in this context. This may be used to determine how far apart a given sample is from every other sample used in the training set. It determines the appropriate goal for each new set of data. The goal value will be calculated as the weighted average of the values set by the k closest neighbours. K's controllable parameter may be proportional to the forecast. When K is tiny, there is a lot of variation and not much of a trend. Low variability and high bias are indicated by a bigger than normal K-valve. The key benefit in this KNN is that it does not need training or optimisation. When making predictions about fresh datasets, this KNN makes advantage of data samples. This results in increased complexity and lengthier execution times.

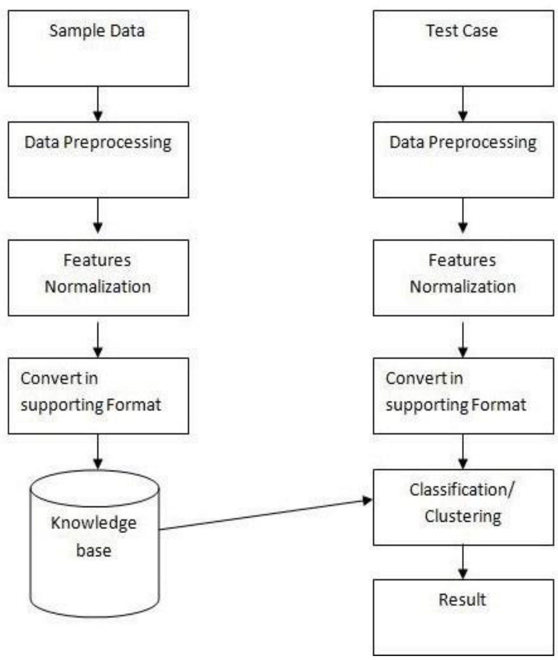

Figure 3.Proposed system Architecture

Here, we start by collecting the data sets, processing the data, and cleaning it, if necessary. After that, the data is normalised if necessary, such as by compressing it. The next step is to transform the information into a usable format. The information is then filed away in databases. The necessary procedure is then carried out. The final outcomes are available now.

4.Data set:

The research data comes from the official government website of India. The data set can be used freely by researchers and academics. The data set covers the years 2000 through 2022 in the Indian state of Maharashtra. The following experimental settings were used for this study. The dataset features a variety of Kharif, Rabi, and fall crops grown in the state of Maharashtra. These include sunflowers, bajara, jowar, time of year, groundnut, rice, cottonseed, tur, and many more. The yield of these crops is measured in lakhs of tonnes per hectare. The government provided dataset includes information that has been checked for outliers and noise. The variables were transformed into both category and numeric formats as needed by the model.

5. Evaluation and Results:

A java programme is developed to estimate agricultural output. The application process consists of three stages. Data management comes first, followed by data testing, and finally data analysis. By organising datasets, we may get datasets from prior years and transform them into a usable format. Because of the use of the Weka tool, all of the datasets included in this undertaking have been transformed into attribute relation files. In the testing phase, we can conduct tests independently. Two machine learning techniques have been discussed. Naive Bayes and the K-Nearest Neighbour Method are two examples. In testing, we can pick any method and undertake testing of datasets, such as obtaining yield results by picking a specific crop, location, and season. In the analysis section, we can load an entire dataset file to compare the two approaches' precision. This aids in foreseeing which approach will prove effective. We used these criteria to determine the most well-known metrics for assessing Prediction algorithms. Accuracy, Precision, and Recall are some of the several Metrics evaluated here for classification. Both algorithms, as well as the Random Forest Algorithm, are tested in this way so that they can be compared to one another. Table 1 displays the final evaluation results.

S.No	Name of the Algorithm	Accuracy(%)	Precision(%)	Recall(%)
1	Naive Bayes	94	92	90
2	KNN	90	87	86
3	Random Forest	87	82	80

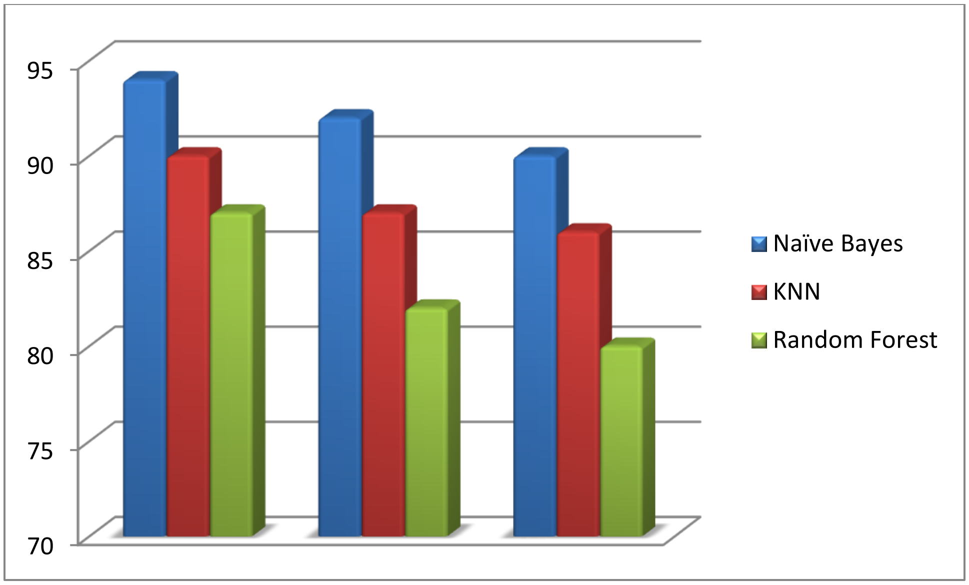

Figure 4.Evaluated Results of the Proposed Algorithms

Figure 4 displays the results of comparing the proposed Naive Bayes algorithm to the state-of-the-art methods of KNN & Random Forest. Our testing indicates that naive bayes performs brilliantly across all scenarios. While the remaining algorithms do a respectable job, there is at least one dataset where naive bayes performs noticeably better.

6. Conclusion:

Like many other sectors, agriculture is currently undergoing a digital transformation. How much information is gathered from farms. There is widespread use of wireless, IoT, artificially intelligent, . Due in large part to the advancements in AI and ML over the past two decades, the agricultural sector has seen a proliferation of new initiatives. Machine learning, neural networks, and deep learning are all subsets of artificial intelligence. So it's important that our farmers are up-to-date on the latest developments in machine learning along with other cutting-edge methods. Using these methods, farmers can increase their agricultural yields significantly. To increase crop yields, farmers are increasingly using machine learning methods. The issues facing agriculture can also be addressed with the aid of these methods. By testing out various algorithms, we can also improve yield accuracy. Therefore, by comparing the results across crops, we can enhance the efficiency. Many areas of farming now use sensor technologies.

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