# Improved Crop Yields and Resource Efficiency in IoT-based Agriculture with Machine Learning

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***Abstract*— Despite popular belief, agricultural research today is more based on hard evidence; exact; precise, and rigorous than ever before. Almost every industry has been disrupted by the spread of IoT-based technologies, including urban planning, healthcare, the electricity grid, the home, and agriculture, frequently referred to as "smart agriculture". Machine learning (ML) and IoT data analytics in agriculture can boost crop yields to meet rising food demand. These revolutionary developments are upending standard agricultural practices and giving rise to new and finest opportunities, but with some drawbacks. Optimal agriculture output requires this research seeks to develop an effective and precise system that uses Crop selection choices made using algorithms that utilize Internet of Things (IoT) sensors and ML Therefore, this paper, proposed an ensemble model using machine learning for crop prediction based on IoT data which is collected from the IoT sensors using the PLX-DAQ tool. There are several suggested machines learning models, including "Naive Bayes, Decision Tree, Random Forest Support Vector Machine, and K-Nearest Neighbour,". According to the experimental findings, ensemble learning had the greatest accuracy of 97.45% for predicting early crop yields. The results of this research will significantly increase the dependence on data for choices relating to climate change and agricultural practices.**

***Keywords—Artificial Intelligence, Internet of Things (IoT), Machine Learning, Smart Farming, Agriculture, Prediction.***

## I. Introduction

In recent years, the proliferation of IoT devices has been meteoric. For this reason, the rapid growth of digital technologies. In the coming ten years, millions of new devices, sensors, and apps will be online thanks to digitally inventive technology. Through network architecture, networked sensors, and devices produce and send a vast amount of data [1][2][3].

The agriculture sector, widely seen as one of the world economy's core strengths, has been crucial to a country's economic growth. With the use of sensors, crops can now be observed on cutting-edge ground thanks to the IoT, which has made it possible to achieve sustainable growth[4]. Future computing and connectivity in agriculture will be facilitated by IoT technology. The agricultural industry has remained stagnant and time-consuming for far too long, but the network of wireless sensors is a formidable and flexible technology with the ability to revolutionize it. too flexible

and smart, hence increasing agricultural production with minimal human input [5][6][7]. As a result, to maintain up with the ever-increasing demand for food, many agricultural procedures will need to be simplified.

Internet of Things-enabled agricultural smart systems and machine learning are being made and used, which is changing the field of agriculture by not only making food output better but also making it more cost-effective. The concept of "smart farming" has lately attracted the focus of numerous researchers due to its potential to improve farmers' ability to manage their fields and crops [8]. A significant improvement in both agricultural product quality and farm life may be possible using today's state-of-the-art means of communication and information storage. While nearly all American farmers utilise some form of smart farming technology, only around a quarter of European farmers do. Increased crop yields with less human effort are possible with the use of intelligent ways of farming that optimise, streamline, and enhance traditional farming methods. Intelligent farming employs a range of IoT sensors that are linked to agricultural machinery, increasing crop yields and providing a beneficial agricultural experience [9].

### *A. Problem Definition*

A farmer may manage his crops and agricultural area in real-time with the help of a high-tech gadget powered by the IoT. A minimum of one of the drawings and/or the textual description thereof provide essential information for understanding this system, and the claims provide additional details. Several devices such as sensors, wireless modules, servers, databases, computers, apps, and control panels for things like water pumps and pipes, alarm systems, buzzers, and surveillance cameras. a system for controlling pesticides and monitoring crop quality, and several unmanned aerial vehicle (UAV) units make up the intelligent system. A variety of factors relating to the crops and the agricultural field are periodically detected by the many sensor units in conjunction with the crops. The programme presents the gathered information to the farmer in a graphical style, so that he or she may assess the state of the crop. For example, when a farmer sends a wireless command from his computer, the water motor and water management system will respond by watering the land automatically. The ultrasonic sensor keeps tabs on how much water is in the container and regulates how much is dispensed onto the soil.

## II. Internet of Things (IoT)

The Internet of Things (IoT) is a state-of-the-art infrastructure that permits the networked wireless connection of devices. As a result, "smart farming" is possible [10]. Many businesses throughout the healthcare, retail, telecommunications, electricity, and agriculture sectors are experiencing the effects of the IoT, which aims to boost productivity and use in all of these areas[11][12][13].

The IoT's consequences and its practises that have not yet been noticed are revealed through current applications. However, if one takes into account how far technology has come, Many aspects of farming may be improved by using IoT technologies, including automated agricultural operations, gathering data, utilizing sensors and smart gadgets, making choices with the aid of artificially intelligent systems stored in the cloud, etc. (Figure 1).

The IoT makes it possible to conduct remote monitoring of living things, including animals and plants, by using data collected from cellular phones. Thanks to sensors and equipment, farmers can forecast yields and analyse the weather with more accuracy [4]. Water harvesting, monitoring and regulating flow volume, assessing water demands of crops, scheduling of supply, and water conservation are all areas where the IoT is becoming increasingly engaged [14]. Based on the needs of the soil and plants, the gateway's built-in sensors and cloud connectivity will allow for remote monitoring of both the status and the water supply [15]. Farmers have reached an important point with the help of IoT technology since they no longer have to personally monitor and analyse each plant for signs of pests, diseases, and nutritional deficiencies.

Based on diverse crop and field kinds, researchers have suggested various methodologies, designs, and equipment to monitor and relay agricultural information at various growth phases[16][17]. For gathering and subsequently disseminating data, several manufacturers offer communication tools, many sensors, robots, large machines, and drones. To protect the safety of the environment and food, food and agricultural organizations work with other governmental organizations to produce rules and regulations governing the usage of technology [18][19].

## III. Literature Review

The agricultural sector is crucial to the development and expansion of the country. Traditional agricultural practices are not technically methodical and are time-consuming operations. As the world moves towards the usage of new technology, it is crucial to implement them into farming. Numerous illnesses significantly reduce agricultural productivity, thus early disease prediction is critical.

The agricultural domain has employed a variety of frameworks in recent years. Internet connectivity, wireless sensor networks, and IoT devices may automate tasks that would otherwise need human labour, optimise resource utilization, and enable farmers to monitor their property much more effectively from a distance [20]. Following a few previous attempts, the following discussion will focus on utilizing machine learning and Internet of Things technology in agricultural contexts[21].

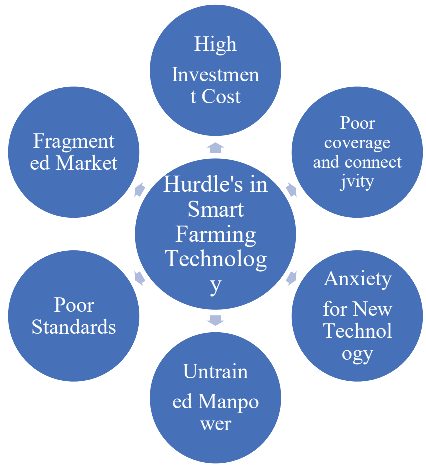


Fig. 1. Obstacles to the use of smart agriculture technologies.

This study was conducted to help in the development of an IoT architecture for use in the agricultural sector [22] Describes the usage of an IoT monitor sensor board for horticulture in the Thiruvarur District of Tamil Nadu for analyzing soil parameters and monitoring the production of tiny and nutritional fibre. The framework aids in the development of trustworthy verdicts through the storage, collection, and analysis of data from the IoT sensors using ML algorithms. The dataset is categorized using the ML model following the NFSM threshold values for specific smaller nutrients and dietary fibre. Several different categorization techniques based on machine learning (ML) might be employed for this. Several popular examples are Naive Bayes (NB), Logistic Regression (LR), Random Tree (RT), and K-Nearest Neighbour (KNN), Measures such as mean absolute error (MAE), root mean square error (RMSE), root relative squared error (RRSE) and relative absolute error (RAE), are used by researchers to evaluate the efficacy of various categorization systems. Mean absolute error (MAE), root-mean-squared error (RRSE), and root-mean- squared error (RMSE), all favour the KNN classifier over the other three, although root-mean-squared accuracy (RAE) favours the RT method over KNN (with a score of 66.24).

This paper [23] provides a lightweight AI-based technique for diagnosing rice leaf disease. In this case, we employ the concept of computing at the edge. We use a Raspberry Pi as our edge device. To analyze all the data we needed, we utilized a Brown Spot, Raspberry Pi, Leaf Blast, and Hispa, which are just a few of the rice plant diseases. diseases that are being investigated.They have retrieved the relevant characteristics from the images after doing the required pre-processing. Then, by incorporating these attributes into several machine learning techniques, we created an image categorization model. The best results were obtained using the Random Forest method. Using our image classification algorithm on our cutting-edge device, we were able to obtain an accuracy of 97.50 percent.

The papers suggest an irrigation system that uses machine learning and the IoT [24] to improve the effectiveness of irrigation. Analogue to digital converters (ADC) is used by the sensors on the Raspberry Pi to measure temperature and soil moisture. Here, it is accomplished via the Serial Peripheral Interface (SPI) protocol. Before being deployed on the Raspberry Pi, an ML model is developed using the Naive Bayes approach. The sprinklers are controlled by the machine learning model, which analyses sensor data with an accuracy of more than 98.33 percent. A working version of the project with a pump for water and a relay is also constructed to show the intricacies of the irrigation system in action.

TABLE I. COMPARISON OF EXISTING IOT FRAMEWORK FOR AGRICULTURE

| Reference | Influence | Outcomes |
|---|---|---|
| Lavanya et al., 2020 [25] | Unique IoT and NPK-based sensors. | This was beneficial to farmers since it increased agricultural yields |
| M. S. Farooq et al., 2019 [26] | For crop monitoring and management, they provide a system based on ML and wireless networks. smart farming using the Internet of Things. | Data mining reveals prompt prediction of safe measures, leading to higher agricultural yields. |
| Agrawal et al., 2019 [27] | The future strategy for gathering agriculturally- relevant data and the resulting smart agricultureplan. | To maintain watch on the crop and anticipate any issuesthat may arise, sensors and cameras have been set up. |
| Rallabandi 2022 [28] | Using technologies like Arduino, Internet of Things, and Wi-Fi, smart farmers may improve | improving the struggling agriculture industry by implementing IoT, Wi-Fi, and smart farming. |
| H. Agrawal et al., 2019 [27] | Low-power electronics and sensors that require constant upkeep. Gateway processors. | The cultivation of precision crops made possible by the Internet of Things; the Calculating duty cycles to minimize wasted power. |
| S. Al-Sahrawi et al., 2017 [29] | They show the top wireless communication standards for the Internet of Things. | The technologies of Connectivity technologies includingZ-Wave, ZigBee, Bluetooth Low Energy (BLE) close- field communication (NFC) as well as the 6LoWPAN wireless standard. easy to use, which is perfect for sustainable farming. |

The use of machine learning and Internet of Things (IoT) technologies in agriculture provides various benefits over traditional approaches. These innovations allow for task automation, resource optimisation, and remote monitoring, all of which improve overall agricultural output. In the context of soil analysis and crop monitoring, the employment of IoT sensor boards and machine learning algorithms helps to collect and analyse critical data, giving farmers with trustworthy insights. Furthermore, the use of AI-based disease diagnosis tools, such as the lightweight strategy that employs edge computing with a Raspberry Pi, allows for the efficient and accurate identification of plant diseases, resulting in early intervention and crop protection. Furthermore, using machine learning in irrigation systems improves precision by analysing sensor data to operate sprinklers, resulting in more accurate water resource management. However, it is critical to recognise limits such as potential upfront expenses, technological infrastructure needs, and the need for experienced individuals to manage and understand the data. Despite these hurdles, the benefits of enhanced efficiency, lower labour costs, and better decision-making make machine learning and IoT integration in agriculture a potential path for long-term development.

## IV. PROPOSED METHODOLOGY

This section discussed the methodology of research work including different research steps such as data collection, preprocessing, splitting, model implementation, performance evaluation and prediction, etc., and also provided a proposed flowchart and algorithm.

### *A. Data Collection*

The term "data collection" is used to describe the systematic act of collecting and examining data and statistics from various sources. Gathering information allows one to remember events and draw conclusions about future occurrences based on commonalities. For this project, we gather data from IoT gadgets in real-time. One component of putting the Iot into action is gathering data from the relevant field. Parameters including soil moisture, air temperature, and pH are tracked at a specific field location. Figure 2 depicts the IoT data-collecting process in action out in the field.

The water content is measured by Arduino's soil moisture sensor because it forms the foundation for supplying fertilizers to the soil. The overall temperature in the field is measured with the support of an LM35 temperature sensor. The DHT22 humidity sensor measures both the relative humidity and air's temperature. Similarly to this, the pH of the soil has to be continuously regulated since it affects the accessibility of soil minerals and the pace of crop development. The pH metre can be used to monitor the pH level. The pH meter may be used to determine the pH level. The sensors are controlled by a microcontroller called the Arduino, which is also used to gather data from the sensors. An Excel file will be used to store the data that was detected via Wi-Fi. The Arduino programme and the Parallax PLX-DAQ data collection tool are employed to save data in an Excel file. Table II displays the IoT sensor data that was gathered using PLX-DAQ.

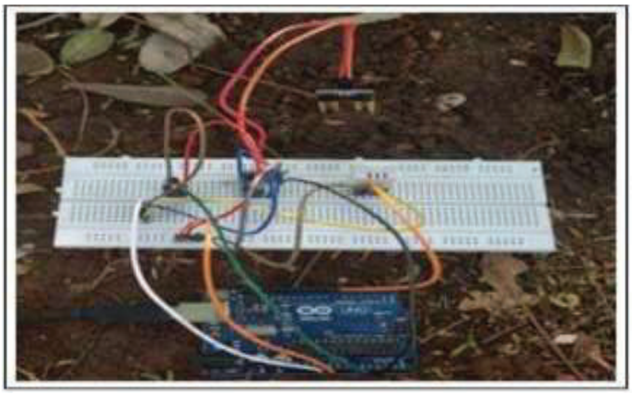

Fig. 2. IoT for Data Collection.

TABLE II. COLLECTED DATA USING PLX-DAQ

| S. No. | Time (AM) | Temperature (C) | Humidity (%) | Moisture (%) |
|---|---|---|---|---|
| 1. | 6:33:34 | 31.25 | 42.4 | 76.54 |
| 2. | 6:33:36 | 31.25 | 42.3 | 83.19 |
| 3. | 6:33:38 | 31.25 | 42.4 | 82.6 |

| | | | | |
|---|---|---|---|---|
| 4. | 6:33:40 | 31.25 | 42.6 | 82.6 |
| 5. | 6:33:42 | 31.25 | 43.5 | 82.21 |
| 6. | 6:33:44 | 31.25 | 43.6 | 82.21 |
| 7. | 6:33:46 | 31.25 | 44 | 81.82 |
| 8. | 6:33:48 | 30.76 | 44 | 81.43 |
| 9. | 6:33:50 | 30.76 | 43.8 | 80.16 |
| 10. | 6:33:52 | 31.25 | 43.5 | 80.45 |
| 11. | 6:33:54 | 31.25 | 43.2 | 80.65 |
| 12. | 6:33:56 | 31.25 | 43 | 80.45 |

### *B. Data Preprocessing*

The term "data preprocessing" is used to describe the processes that get raw data prepared for analysis by learning algorithms. Since ML cannot analyze noisy data, pre-processing is an essential step. In this phase of data preparation, the encoding procedure takes place. Feature rescaling, sometimes referred to as min-max scaling or min-max normalization, is one technique for adjusting the scales of a set of features. When dealing with numerical characteristics, this feature rescaling technique is the easiest one to use.

### *C. Data Splitting*

A data splitting, which separates a dataset into two distinct parts, a training set and a test set. Data splitting is a crucial step for developing models in the field of data science. Through this procedure, data models and the processes that rely on them may be built with confidence [30]. Models are developed, tweaked, and trained with the use of the training dataset. Two common applications of training sets are parameter estimation and comparing models' results. 80 percent of the data may be utilized for training, and 20 percent can be used for testing, according to the conventional ratio of 80:20.

### *D. Machine Learning (ML) Models*

Several analyses have shown that ML is an essential decision-support tool for forecasting agricultural output. Machine learning can be a tool that may help farmers save money by providing them with in-depth guidance and insights on their crops. Nave Bayes, Decision Tree, the Support Vector Machine, the K-Nearest Neighbor, Random Forest, and machine learning models are studied here.

#### *1) Decision Tree*

DT are one kind of classification method that may be utilized in ML. The educational decision tree is the foundation for inductive learning. The data or observations are shaped into a model based on a set of criteria. The plan is to deduce a universal law from the specific cases that have already been seen. As a result, if the target characteristic is either unique or stable, decision trees may carry out two separate operations [31].

#### *2) Naïve Bayes*

The naïve Bayes approach utilises Bayes' theorem, with the assumption that features are unrelated. It works well with both binary and multi-class data and has many practical applications, including text classification, spam filtering, document categorization, and more. The neural network (NB) classifier may be used to quickly categorise data outliers and develop an accurate prediction model [32].

#### *3) Support Vector Machine*

SVM is a supervised machine learning method that is applied in applications for classification and regression. It determines the ideal hyperplane for separating data into multiple classes by maximizing the margin between them. Through the kernel method, SVM can handle high-dimensional data and is effective when dealing with both linearly separable and non-linearly separable datasets. However, SVM's effectiveness decreases when the amount of noise in the data set increases, as happens when target classes overlap.

#### *4) K-Nearest Neighbor*

The K-Nearest Neighbours (KNN) method is a form of learning that can do "instance-based learning" or "non-generalizing learning." All training cases remain in an n-dimensional space rather than focused on constructing a generic internal model. Similarity metrics (such the Euclidean distance function) provide the basis of KNN's classification of unstructured data [33].

#### *5) Random Forest*

One well-liked machine learning method that relies on the supervised learning technique is called Random Forest. Classification and regression are only two of its many applications in machine learning. Random Forest is a type of classifier that gets its name from the fact that it employs an "ensemble of decision tree"s trained on separate subsets of a dataset before averaging the results to increase prediction accuracy [34].

### *E. Proposed Algorithm and Flowchart*

**Algorithm 1:** Proposed Algorithm

**Input:** IoT Dataset
**Output:** Crop Prediction

**Steps:**
**Step 1:** Collect and input the IoT dataset which is collected from the different IoT devices.
**Step 2:** Preprocess the data in the data preprocessing including some steps i.e.,

- Data encoding
- Fill missing values
- Feature scaling.

**Step 3:** Perform data splitting into two different steps such as the training and testing set.
**Step 4:** Implement and train the following machine learning models:

- K-Nearest Neighbor
- Naïve Bayes
- Decision Tree
- Support Vector Machine
- Random Forest

**Step 5:** Generated crop suggestion prediction model from the testing.

- Accuracy, recall, F1-score, precision, etc. are only a few of the performance measures that may be used to assess the effectiveness of the suggested models.

**Step 6:** Finally, predict the crops.

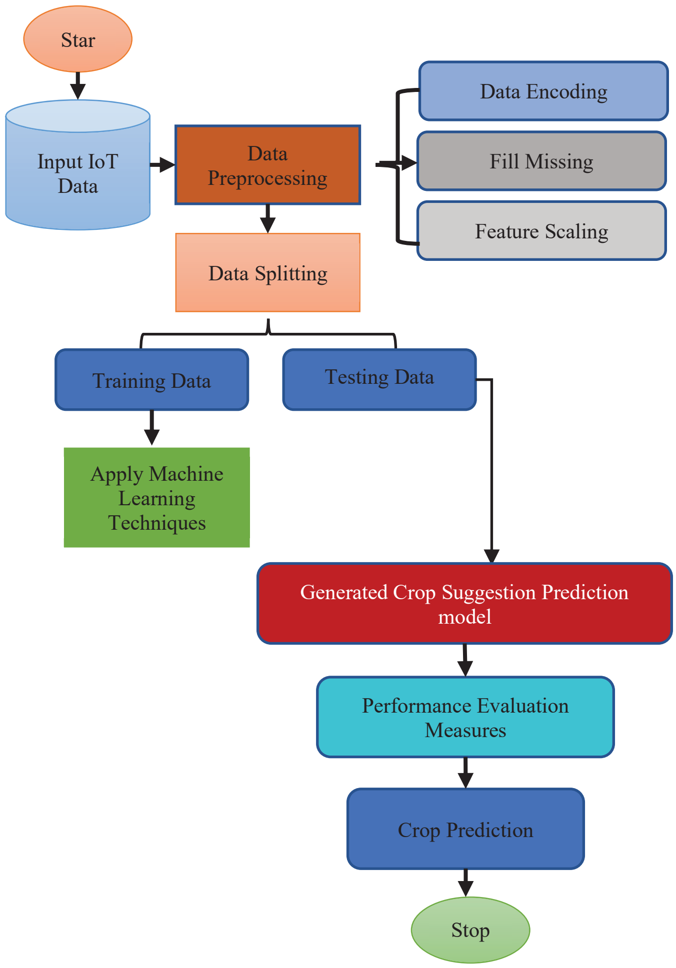


Fig. 3. Block Diagram of the Proposed System.

## V. Results and Analysis

This section illustrates the simulated results and discussion of the research work, as well as comparisons between existing and proposed models.

### *A. Simulated Results*

Here, we have presented some experimented results of the proposed machine learning models with different graphs and tables.

Figure 4 illustrates the accuracy results of many machine learning algorithms. The percentage of accurate predictions is plotted along the y-axis, while the various machine learning models are presented along the x-axis. Among the three options, the random forest model has the highest accuracy (99%).

TABLE III. Performance Results of the Proposed Machine Learning Models

| Models | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Decision Tree | 96.25 | 97 | 96 | 96 |
| Naïve Bayes | 96.90 | 97.54 | 97 | 97 |
| Support Vector Machine | 94.17 | 94.26 | 94 | 94.25 |
| K-Nearest Neighbor | 92.97 | 93.88 | 93 | 93.47 |
| Random Forest | 99 | 100 | 89 | 94 |
| Ensemble Learning | 97.34 | 97 | 97.98 | 97.45 |

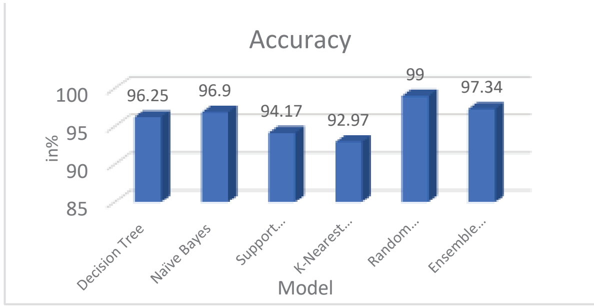


Fig. 4. Accuracy Results of the Different Models.

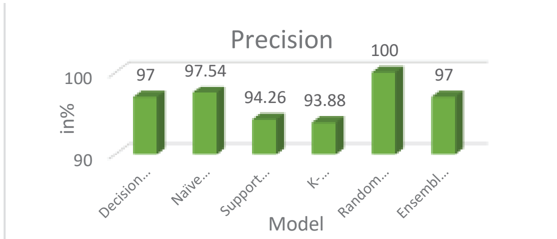


Fig. 5. Precision Results of the Different Models.

Figure 5 above illustrates the accuracy outcomes of several ML methods. The models used for ML are represented by the x-axis in this graph, and the accuracy values are shown as percentages on the y-axis. Among all these models, the random forest has the highest 100% precision, and the naïve Bayes has 97.54%, decision tree, and ensemble learning has 97% value, and so on.

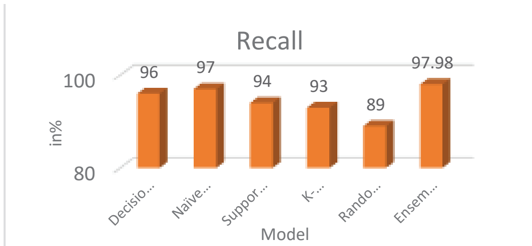


Fig. 6. Recall Results of the Different Models

Figure 6 demonstrates the recall results of various machine-learning models. The x-axis of this graph depicts the machine learning models, whereas the y-axis shows the recall percentages. Among all these models, the ensemble learning obtained a 97.98% recall value which is the highest score of the others.

Figure 7 above displays the f1-score outcomes from several machine learning algorithms. The models based on machine learning are shown on the x-axis in this graph, and the percentage values of the f1-scores are shown on the y-axis. Among all these models, the ensemble learning obtained a 97.45% f1-score value which is the highest score of the others.

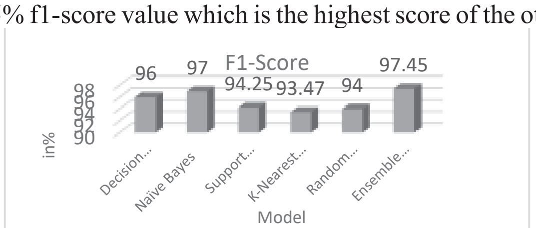


Fig. 7. F1-Score Results of the Different Models

### B. Comparison and discussion

This section discusses the comparisons with several crops, including rice, maize, and bananas, with many characteristics, including pH, nitrogen, potassium, and other elements.

Additionally, based on the model's accuracy, other machine learning techniques from earlier studies including Naive Bayes, Decision Tree, Gaussian Naive Bayes, Random Forest, XGBoost and K-Nearest Neighbours, were also assessed.

TABLE IV. CROPS RECOMMENDED FOR DIFFERENT CONDITIONS

| Year | References | Crop | N | P | K | pH |
|---|---|---|---|---|---|---|
| 2021 | Shetty and Smitha [35] | Rice | 80 | 40 | 40 | 5.5 |
| | | Maize | 80 | 40 | 20 | 5.5 |
| | | Banana | 100 | 75 | 50 | 6.5 |
| 2023 | S. Sundaresan et al. [36] | Rice | 90 | 42 | 43 | 6.5 |
| | | Maize | 71 | 54 | 16 | 5.7 |
| | | Banana | 117 | 76 | 47 | 6.1 |

The above table 4 shows the table which represents some recommended crops i.e., rice, maize, and banana with respect to the different features like nitrogen (N), potassium (K), phosphorus (P), and pH, etc. According to this table, in 2021, the highest pH value for banana crop is given, and in 2023, the highest pH value for rice crop is given.

TABLE V. ACCURACY COMPARISON WITH DIFFERENT MACHINE LEARNING METHODS

| Year | Ref. | Method | Accuracy (%) |
|---|---|---|---|
| 2022 | Ikram et al. [37] | Gaussian Naïve Bayes (GNB) | 97 |
| 2022 | R. Kumar and V. Singhal [38] | XGBoost (XGB) | 92 |
| 2021 | S. Parween et al. [39] | Naïve Bayes (NB) | 96 |
| 2021 | M. H. Kishan Das et al. [34] | Decision Tree (DT) | 97 |
| NA | Proposed Model | Ensemble Learning (DT, NB, SVM, KNN, and RF) | 97.45 |

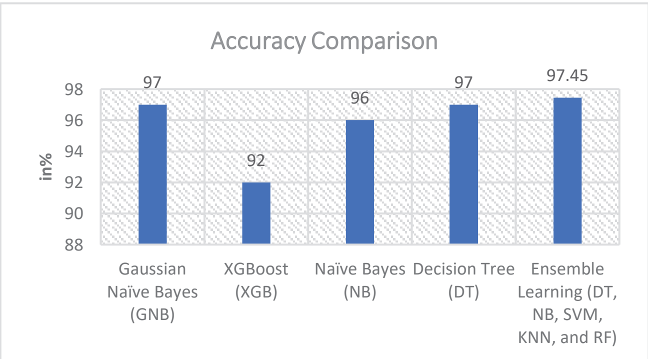


Fig. 8. Accuracy Comparison Graph.

The following table 5 and Figure 8 shows the comparative results of several studies or research papers, along with the corresponding machine learning methods such as GNB, XGB, NB, and DT with the proposed ensemble learning model and their reported accuracy percentages. According to this figure, and table, all machine learning algorithms perform well with the highest accuracy but our proposed ensemble learning model (NB, DT, KNN, RF, and SVM) outperformed the other ML algorithms with 97.45% accuracy.

## VI. CONCLUSION

In a world with a rising population, IoT devices and AI software are helping farmers transform their old methods into smart farming. It takes a lot of human labour to complete each operation involved in conventional farming, including weeding, irrigation, soil maintenance, crop monitoring, spraying pesticides and herbicides, and harvesting. By using the most recent advances to optimise agricultural resources, smart agriculture aims to achieve accurate farming, higher crop quality, and crop quantity. This study includes details on IoT-based systems utilized in previous years. This paper proposed a crop forecasting system by using ensemble machine learning approaches in which DT, NB, SVM, KNN, and RF are included. This study is assessed by analysing data obtained from IoT sensors utilizing the PLX-DAQ analytics application. The performance of these models may be measured in a variety of ways. Figure 3 is a block diagram of the proposed system's working steps. The overall accuracy of the proposed ensemble model is 97.45% rather while the individual machine learning model has achieved the highest 96.25% for DT, 96.90% for NB, 94.17% for SVM, 92.97% for KNN, 99% for RF, and 97.34% for ensemble learning, respectively.

In the near future, the agricultural industry will be transformed to smart agriculture, so there would be no reduction in productivity, yields, or quality, as the agricultural industry progresses to AI, IoT-based Precision farming.

## REFERENCES

[1] J. Lin, W. Yu, N. Zhang, X. Yang, H. Zhang, and W. Zhao, “A Survey on Internet of Things: Architecture, Enabling Technologies, Security and Privacy, and Applications,” *IEEE Internet Things J.*, vol. 4, no. 5, pp. 1125–1142, Oct. 2017, doi: 10.1109/JIOT.2017.2683200.

[2] Gao T., Chen Z., Luo A., Liang R., Yue D., Aventina O., Ran X., Xiao H., Wu W."A Summary of Research on Key Technologies of Precision Agriculture in Green Ecological Tea Garden" International Journal of Emerging Technology and Advanced Engineering, Vol. 9 Issue 9, pp. 45 - 53, Sept 2019

[3] S. Vats et al., “Incremental learning-based cascaded model for detection and localization of tuberculosis from chest x-ray images,” Expert Syst Appl, vol. 238, p. 122129, Mar. 2024, doi: 10.1016/J.ESWA.2023.122129.

[4] V. Rohilla, S. Chakraborty, and M. Kaur, “An Empirical Framework for Recommendation-based Location Services Using Deep Learning,” *Eng. Technol. Appl. Sci. Res.*, 2022, doi: 10.48084/etasr.5126.

[5] V. Sharma, R. B. Patel, H. S. Bhadauria, and D. Prasad, “Policy for planned placement of sensor nodes in large scale wireless sensor network,” KSII Trans. Internet Inf. Syst., vol. 10, no. 7, pp. 3213–3230, 2016.

[6] J. Devare and N. Hajare, “A Survey on IoT Based Agricultural Crop Growth Monitoring and Quality Control,” 2019. doi: 10.1109/ICCES45898.2019.9002533.

[7] M. R. Mohd Kassim, I. Mat, and A. N. Harun, “Wireless sensor network in precision agriculture application,” 2014. doi: 10.1109/CITS.2014.6878963.

[8] Khatraty Y.B., Nauwynck N.M., Diallo M.T., Nanne M.F."Deep Predictive Models Based on IoT and Remote Sensing Big Time Series for Precision Agriculture" International Journal of Emerging Technology and Advanced Engineering, Vol. 12, Issue 11, pp. 79 - 88, Nov.2022, DOI: 10.46338/ijetae1122_09

[9] A. A. S. Aliar, J. Yesudhasan, M. Alagarsamy, K. Anbalagan, J. Sakkarai, and K. Suriyan, “A comprehensive analysis on IoT based smart farming solutions using machine learning algorithms,” *Bull. Electr. Eng. Informatics*, vol. 11, no. 3, pp. 1550–1557, 2022, doi: 10.11591/eei.v11i3.3310.

[10] K. A. Patil and N. R. Kale, “A model for smart agriculture using IoT,” 2017. doi: 10.1109/ICGTSPICC.2016.7955360.

[11] P. Rawat, M. Bajaj, S. Vats and V. Sharma, "ASD Diagnosis in Children, Adults, and Adolescents using Various Machine Learning Techniques," 2023 International Conference on Device Intelligence, Computing and Communication Technologies, (DICCT), Dehradun, India, 2023, pp. 625-630, doi: 10.1109/DICCT56244.2023.10110166.

[12] Barroso-Maza C., Lucas-Córdova J., Sotomayor-Beltran C. "Design of a Sugarcane Diseases Recognition System Based on GoogLeNet for a Web Application" International Journal of Emerging Technology and Advanced Engineering, Vol. 12, Issue 9, pp. 74 - 82, Sept 2022, DOI: 10.46338/ijetae0922_08

[13] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow, and M. N. Hindia, “An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges,” *IEEE Internet Things J.*, 2018, doi: 10.1109/JIOT.2018.2844296.

[14] W. Yong *et al.*, “Smart Sensors from Ground to Cloud and Web Intelligence,” *IFAC-PapersOnLine*, vol. 51, no. 17, pp. 31–38, 2018, doi: 10.1016/j.ifacol.2018.08.057.

[15] M. S. Mekala and P. Viswanathan, “A Survey: Smart agriculture IoT with cloud computing,” in *2017 International conference on Microelectronic Devices, Circuits and Systems (ICMDCS)*, Aug. 2017, pp. 1–7. doi: 10.1109/ICMDCS.2017.8211551.

[16] A. Agarwal, S. Vats, R. Agarwal, A. Ratra, V. Sharma and L. Gopal, "Sentiment Analysis in Stock Price Prediction: A Comparative Study of Algorithms," 2023 10th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2023, pp. 1403-1407.

[17] Nguyen X.-T., Pham L.M. "Detecting Multiple Perturbations on Swine using Data from Simulation of Precision Feeding Systems" International Journal of Emerging Technology and Advanced Engineering, Vol. 12, Issue 12, pp. 136 - 145, Dec. 2022, DOI: 10.46338/ijetae1222_15

[18] Abu N.S., Bukhari W.M., Ong C.H., Sukhaimie M.N., Wibowo S., Kassim A.M. "Automated Agricultural Management Systems Using Smart-Based Technology" International Journal of Emerging Technology and Advanced Engineering, Vol. 12 Issue 5, pp. 123 - 131, May 2022, DOI: 10.46338/ijetae0522_14.

[19] Olawuyi O.J., Oladele D.D. "Investigation of aneuploidy in germplasm of African Yam Bean (Sphenostylis Stenocarpa Hochst. Ex A. Rich) harms using pollen and mitotic data", International Journal of Emerging Technology and Advanced Engineering, vol. 10 Issue 5, pp. 1 - 5, May 2020

[20] A. Giri, S. Dutta, and S. Neogy, “Enabling agricultural automation to optimize utilization of water, fertilizer and insecticides by implementing Internet of Things (IoT),” in *2016 International Conference on Information Technology (InCITe) - The Next Generation IT Summit on the Theme - Internet of Things: Connect your Worlds*, Oct. 2016, pp. 125–131. doi: 10.1109/INCITE.2016.7857603.

[21] Hassan E.I., Ibrahim M.A.S., Mohamed I.E. "Effect of cultivar performance on conservation agriculture on sorghum yield in rain-fed areas, Sennar State, Sudan", International Journal of Emerging Technology and Advanced Engineering, Vol. 10, Issue 9, pp. 19 - 29, Spet. 2020, DOI: 10.46338/ijetae0920_04

[22] G. N. Ahmed and S. Kamalakkannan, “Micronutrient Classification in IoT Based Agriculture Using Machine Learning (ML) Algorithm,” in *2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, Jan. 2022, pp. 1–9. doi: 10.1109/ICSSIT53264.2022.9716293.

[23] S. M. Shahidur Harun Rumy, M. I. Arefin Hossain, F. Jahan, and T. Tanvin, “An IoT based System with Edge Intelligence for Rice Leaf Disease Detection using Machine Learning,” in *2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*, Apr. 2021, pp. 1–6. doi: 10.1109/IEMTRONICS52119.2021.9422499.

[24] S. M. Shahriar, H. I. Peyal, M. Nahiduzzaman, and M. A. H. Pramanik, “An IoT-Based Real-Time Intelligent Irrigation System using Machine Learning,” in *2021 13th International Conference on Information & Communication Technology and System (ICTS)*, Oct. 2021, pp. 277–281. doi: 10.1109/ICTS52701.2021.9608813.

[25] L. G, R. C, and G. P, “An automated low cost IoT based Fertilizer Intimation System for smart agriculture,” *Sustain. Comput. Informatics Syst.*, vol. 28, p. 100300, Dec. 2020, doi: 10.1016/j.suscom.2019.01.002.

[26] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, “A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming,” *IEEE Access*, vol. 7, pp. 156237–156271, 2019, doi: 10.1109/ACCESS.2019.2949703.

[27] K. Agrawal and N. Kamboj, “Smart Agriculture Using IOT: A Futuristic Approach,” *Int. J. Inf. Dissem. Technol.*, vol. 9, no. 4, p. 186, 2019, doi: 10.5958/2249-5576.2019.00036.0.

[28] G. Rallabandi, S. Pavani, K. K. Gulhare, and P. K. Mishra, “Smart advanced agriculture system in India using IoT technology,” *Int. J. Health Sci. (Qassim).*, pp. 10120–10126, May 2022, doi: 10.53730/ijhs.v6nS2.7645.

[29] Maria M., Mehdi A., Ahmed H."Reduction of the Hyperspectral Images Dimensionality using a NewGenetic Algorithm Procedure" International Journal of Emerging Technology and Advanced Engineering, Vol 12 Issue 4, pp. 130 - 141, April 2022, DOI: 10.46338/ijetae0422_16

[30] V. R. Joseph, “Optimal ratio for data splitting,” *Stat. Anal. Data Min. ASA Data Sci. J.*, vol. 15, no. 4, pp. 531–538, Aug. 2022, doi: 10.1002/sam.11583.

[31] A. Tatapudi and P. Suresh Varma, “Prediction of crops based on environmental factors using iot & machine learning algorithms,” *Int. J. Innov. Technol. Explor. Eng.*, 2019, doi: 10.35940/ijitee.A4695.119119.

[32] G. Chhabra, E. M. Onyema, S. Kumar, M. Goutham, S. Mandapati, and C. Iwendi, “Human emotions recognition, analysis and transformation by the Bioenergy Field in smart grid using image processing,” Electronics, vol. 11, no. 23, p. 4059, 2022.

[33] K. Joshi, M. Kumar, M. Memoria, P. Bhardwaj, G. Chhabra, and D. Baloni, “Big Data F5 load balancer with Chatbots framework,” Rising Threats in Expert Applications and Solutions, pp. 709–717, 2022.

[34] H. Kishan Das Menon, D. Mishra, and D. Deepa, “Automation and integration of growth monitoring in plants (with disease prediction) and crop prediction,” 2020. doi: 10.1016/j.matpr.2021.01.973.

[35] S. Shetty and A. B. Smitha, “Smart Agriculture Using IoT and Machine Learning,” pp. 1–16, 2021, doi: 10.1007/978-981-16-6124-2_1

[36] S. Sundaresan et al., “Machine learning and IoT-based smart farming for enhancing the crop yield Machine learning and IoT-based smart farming for enhancing the crop yield,” 2023, doi:

[37] A. Ikram *et al.*, “Crop Yield Maximization Using an IoT-Based Smart Decision,” *J. Sensors*, 2022, doi: 10.1155/2022/2022923.

[38] R. Kumar and V. Singhal, “IoT Enabled Crop Prediction and Irrigation Automation System Using Machine Learning,” *Recent Adv. Comput. Sci. Commun.*, 2020.

[39] S. Parween, A. Pal, I. Snigdh, and V. Kumar, “An IoT and Machine Learning-Based Crop Prediction System for Precision Agriculture,” 2021. doi: 10.1007/978-981-16-1550-4_2.