International Journal for Innovative Engineering and Management Research

PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL

www.ijiemr.org



IJIEMR Transactions, online available on 20th Sept 2023. Link

:http://www.ijiemr.org/downloads.php?vol=Volume-12&issue=Issue 09

**10.48047/IJIEMR/V12/ISSUE 09/29**

Title **A Smart Agriculture Framework with Machine Learning based Crop Selection and Auto-Irrigation**

Volume 12, ISSUE 09, Pages: 235-250

Paper Authors **Mr. S. Praveen kumar**

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

# A Smart Agriculture Framework with Machine Learning based Crop Selection and Auto-Irrigation

1. **Mr. S. Praveen kumar**, Assistant Professor, Department of ECE,JNTUH University college of engineering, Jagtial, Telangana, India. praveenkumar_00019@yahoo.com

**Abstract**

IoT-based savvy horticulture is an original methodology that utilizations organized sensors and gadgets to expand crop creation and upgrade cultivating rehearses. To give ranchers reasonable bits of knowledge, it contains getting information from different sensors, including soil dampness, temperature, stickiness, and weather conditions station sensors. The information is then examined utilizing machine learning algorithms. Shrewd horticulture fueled by IoT can likewise save costs and increment efficiency for ranchers. Ranchers can bring down work costs and assurance steady and right info application via mechanizing a few cycles, such treatment and water system. Moreover, ranchers can limit crop misfortunes and lift income by speedily recognizing and resolving potential issues by watching out for ecological circumstances progressively. To augment farming efficiency and protect assets, two critical advances in present day horticulture are machine learning based savvy water system and brilliant harvest choice. Brilliant harvest choice chooses crops that are generally fit to the nearby climate and can give the greatest returns for ranchers by breaking down information on soil conditions, weather conditions, verifiable yield yields, and market request utilizing machine learning algorithms. Brilliant water system utilizes machine learning algorithms to adjust water system plans in light of soil dampness, weather conditions, and plant water interest to diminish water misfortune and lift crop efficiency and quality. At the point when consolidated, these advancements can uphold ranchers in guaranteeing economical and compelling agribusiness, safeguarding assets, going with information driven choices, and adjusting to changing ecological circumstances.

**Keywords:** Crop Selection, Irrigation, Machine Learning, Internet of Things, Smart Agriculture.

## 1. Introduction

The expression "accuracy horticulture," some of the time known as "shrewd cultivating" or "satellite cultivating," alludes to a cutting edge way to deal with oversee farming area that expands crop yield while limiting unfavorable consequences for the climate [1]. It incorporates a large number of state of the art strategies and instruments, for example, wise water system frameworks and yield choice, which are indispensable to the most common way of changing conventional cultivating techniques into ones that are unquestionably proficient and economical.

Crop determination is a vital part of accuracy horticulture since it includes distinguishing the harvests that will yield the best outcomes in a specific region while representing factors like soil quality, environment, and customer interest. Contemporary information examination, remote detecting, and geographic data frameworks (GIS) empower ranchers to settle on informed conclusions about the harvests that have a place on their territory [2]. This strategy supports expanding profit, boosting yield, and disposing of asset squander.

The significance of harvest choice with regards to accuracy horticulture couldn't possibly be more significant. Ranchers should pick crops that can get through these difficulties and sort out some way to adjust to the results of environmental change, as well as moving atmospheric conditions and limited normal assets. By picking crops that are appropriate to the neighborhood climate, ranchers can bring down the dangers related with unexpected climate events, a lack of water, and bug episodes. Also, picking crops serious areas of strength for with request guarantees that farming endeavors will keep on being practical and yield better monetary returns.

The utilization of current water system frameworks is one more critical part of accuracy horticulture that fundamentally adds to harmless to the ecosystem crop creation [3]. Customary water system strategies much of the time make the harvest be either overwatered or underwatered, bringing about water squander, diminished crop quality, and expanded creation costs. Shrewd water system frameworks consolidate sensor innovation, climate information, and ongoing checking to definitively convey water when and where it is required.

On account of the utilization of savvy water system frameworks, ranchers can now augment their utilization of water, limit their utilization of assets, and advance the improvement of plants under ideal circumstances [4]. By persistently checking the dirt's dampness content, the climate, and the plants' water necessities, ranchers can adjust water system plans. This ensures that harvests get the perfect amount of dampness — neither a lot of nor excessively little. As well as expanding crop yields and quality, this level of water system accuracy decreases generally speaking energy utilization and mitigates the hindering outcomes that agribusiness has on the climate.

Accuracy farming, enveloping yield determination and insightful water system frameworks, is expected because of the squeezing need to address the flow difficulties confronting the agribusiness area. A developing number of individuals, a diminishing measure of arable land, and a developing worldwide populace have made it important to utilize state of the art innovation that could raise rural efficiency while decreasing the harming impacts that cultivating has on the climate.

Accuracy agribusiness has undeniably a larger number of utilizations than customary cultivating strategies. artificial intelligence (AI), Machine learning (ML), and huge information investigation (enormous information examination) cooperate to give ranchers significant experiences into crop wellbeing, sustenance the board [5], bug control, and yield conjectures. With the utilization of this data, ranchers can upgrade asset use, settle on information driven choices, and at last raise the manageability and generally speaking efficiency of their homesteads.

## 2. Literature

For the target of anticipating rural creation and dry season conditions, Nermeen Gamal Rezk et al. [1] came up with a shrewd procedure in view of the blend of a covering highlight

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

determination approach and a Section order technique. The assessing methodology for the recommended procedure utilizes five particular datasets. Considering the outcomes, it was reasoned that, in contrast with the all around utilized systems, the proposed technique is strong, precise, and right in its grouping and gauge of rural creation and dry spell.

To resolve gives that surface during the pre-reap, gathering, and post-collect phases of the agrarian creation process, Vishal Meshram et al. [2] gave an exhaustive investigation of the latest uses of AI in horticulture. By utilizing machine learning, cultivating might be done all the more unequivocally and effectively with less work force while as yet creating great items. machine learning is utilized to make this conceivable.

A far reaching survey of machine learning strategies applied in the beyond a decade for the genomic choice of single and different characteristics in significant harvest species was given by Hao Tong et al. [3]. The creators underscore the significance of building demonstrating devices that could prompt further headways in genomic determination, as well as social affair information on middle of the road aggregates, like degrees of protein, metabolite, and quality articulation. Moreover, they offer an intensive assessment of the elements impacting genomic determination, zeroing in particularly on how well models move to various conditions.

Crafted by Dilli Paudel et al. [4] focused on the making of elements or indicators that might be made sense of (as for the development and advancement of harvests), as well as the utilization of AI that jelly information. The aftereffects of yield reproductions were joined with climate, soil, and remote detecting information from the MCYFS data set to make new highlights. They had the option to grasp the associations between the three components all the more obviously subsequently. They put a great deal of exertion into making a strategy that was reusable and secluded so that, with just little design transforms, it very well may be utilized for a scope of harvests and nations.

A. N. A multi-class order model was made accessible by Deepa et al. [5] as a device to assist ranchers with concluding which yields to establish on a specific real estate parcel. The three principal parts of the model are the age of order runs, the change of constant information into fluffy qualities, and the registering of loads for the factors. The fitting relative loads of the factors are set utilizing a strength based harsh set technique. To transform persistent information into fluffy qualities, they are initial put through a fluffy vicinity connection. Utilizing the bijective delicate set approach, the order standards for the five farming yields — rice, groundnut, sugarcane, cumbu, and ragi — are given.

Utilizing a bunch of Sentinel-2 pictures, Mmamokoma Elegance Maponya et al. [6] analyzed the planning capacities of many machine learning models, including SVM (support vector machine), DT (decision tree), k-NN (k-nearest neighbor), RF (random forest), and ML (maximum likelihood). Various blends of photograph sets were utilized in the four examinations that were directed. In the initial three trials, one sort of picture was utilized: 1) single-day photos, generally known as "uni-transient" pictures; 2) sets of five pictures chosen physically founded on the different phases of harvest development; and 3) mixes of five pictures chose from among the top single-date pictures. In the fourth preliminary, the

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

calculations were tried with exclusively pre-reap photographs, adding pictures in sequential request of when they were taken. Figuring out how right off the bat in the season it is feasible to accomplish palatable precision was the point of this analysis.

G. Seetharaman et al. [7] utilized the Internet of Things (IoT) to distinguish and categorize peanut leaf illnesses in real time using mixed machine learning techniques (GLD-HML). To begin with, the creators partition the leaf's evil region utilizing the improved crow search (ICS) approach, which is a critical stage in the characterization of problems. During the element extraction stage, they give a multi-objective sunflower enhancement (MSO) strategy to choose the best highlights from various separated highlights. Then, they show the utilization of many classes in a moth enhancement based moth optimization-based deep neural network (MO-DNN) for illness recognizable proof in groundnut leaves.

A few major homesteads in Western Australia filled in as a contextual investigation for Patrick Filippi et al's. research, which included yield screen information from wheat, grain, and canola crops from three separate seasons (2013, 2014, and 2015), covering about 11,000 to 17,000 hectares every year. In light of the area and season of day of every perception point, relevant indicator factors were produced for every one after the yield information were handled into a 10-meter-square matrix. Then, to demonstrate the yield, the information were incorporated to a spatial goal of 100 meters. Utilizing the accessible information, irregular woods models were utilized to figure the harvest yields of canola, wheat, and grain. Three unmistakable models were made: one for pre-planting conditions, one for mid-season conditions, and one for late-season conditions. The motivation behind this exploration was to inspect the way that the model's prescient limit adjusted as new information from inside the season opened up. Also, these periods line up with the seasons wherein choices about administration, such as applying manure, are made.

Support Irregular Woods is an original half breed relapse based calculation that outflanks conventional AI procedures like profound Q-learning, choice trees, slope helping, arbitrary backwoods, and counterfeit brain organizations. Dhivya Elavarasan et al. [9] proposed utilizing Support Arbitrary Woodland. To boost the usage of accessible examples, the novel methodology applies support learning at each parting trademark choice during tree building. They break down the variable importance measure to figure out which variable is generally significant for hub parting during the model structure process and to advance effective utilization of preparing information. Our coordinated half and half procedure gives a critical improvement over scanty model designs when contrasted with existing strategies. The proposed technique integrates interior get approval as well as lessens over-fitting, speeds up calculation, and improves perceivability.

To achieve clever cultivating, Vijayakumar Ponnusamy et al. [10] focused on the utilization and showing of such state of the art innovation. Savvy cultivating, frequently known as shrewd farming, is the horticultural discipline of integrating information examination and AI into one's activities. Creating and executing a dynamic emotionally supportive network that can assist with rural tasks the board is the point of the "savvy horticulture" development.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Using the latest specialized advancements, for example, machine learning (ML) algorithms, augmented reality (AR) systems, unmanned aerial vehicles (UAV), and the Internet of Things (IoT), may improve precision smart agriculture.

## 3. Proposed Method

The practice of agriculture is among the most fundamental and ancient human endeavors. Choosing which crops to plant on a farm is a crucial decision that farmers must make often. This process is known as crop selection. It establishes the profitability, sustainability, and success of agricultural methods. The significance of crop selection in agriculture, the variables that farmers take into account when selecting crops, and some instances of effective crop selection will all be covered in this essay.

### 3.1 Machine Learning for Crop selection

Machine learning is a useful tool in many industries, including agriculture. Machine learning can be applied to crop selection to help farmers choose which crops to sow on their farms by analyzing vast amounts of data.

**a) Crop Selection Criteria**

- **Nitrogen**

Nitrogen is one of the most important components for the growth and development of plants. It is an essential component of many molecules, such as proteins, amino acids, nucleic acids, and chlorophyll, that are required for development, reproduction, and photosynthesis. Because it affects the type and quantity of crops that may be cultivated in a given soil type and climate, nitrogen is also an important consideration when choosing crops.

- **Phosphorus**

Phosphorus is another essential component for the growth and development of plants. Transmission of energy, cell division, synthesis of DNA and RNA, and root formation all depend on it. Because it affects the type and quantity of crops that can be cultivated in a specific soil type and climate, phosphorus is also an important component in crop selection.

- **Potassium**

Another nutrient that is crucial for the growth and development of plants is potassium. It's essential for controlling the water balance in plants, promoting the activity of enzymes, and preserving plant structure. Because it affects the type and quantity of crops that can be cultivated in a specific soil type and climate, potassium is also an important element in crop selection.

- **Temperature**

Given that temperature has an impact on crop growth, development, and yield, temperature is a crucial consideration in crop selection. Every crop has a preferred temperature range within

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

which to develop, and extremes in temperature can negatively affect the production and growth of plants.

- **Humidity**

Because humidity has an impact on crop growth, development, and yield, it is a crucial consideration in crop selection. Every crop has a preferred humidity range within which to grow, and excessively high or low humidity levels might hinder plant development and yield.

- **ph**

Because pH influences the availability of nutrients in the soil, which in turn influences crop growth, development, and yield, pH is a crucial consideration when choosing crops. Every crop grows most effectively in a particular pH range; pH values outside of this range might hinder plant development and yield.

- **Rain fall**

Rainfall has a direct impact on plant development and productivity, making it a significant component in crop selection. Every crop develops best within a certain range of rainfall, and too little or too much rain can negatively affect plant development and output.

**3.2 Smart Irrigation**

Savvy water system is a state of the art strategy for water the board that utilizes innovation to expand how much water utilized for finishing and farming. This technique watches out for soil dampness levels and water use by utilizing sensors, climate data, and different sorts of innovation. It further develops crop yields, monitors water, and brings down costs by engaging ranchers and exterior decorators to adjust water system plans, water sums, and conveyance strategies in light of ongoing information.

Using sensors, brilliant water system frameworks assemble data on soil dampness, temperature, and meteorological elements. These sensors are situated purposely in the dirt to check the water content open to plants and distinguish when they should be watered more. Through correspondence with a focal control framework, they can change watering levels and water system plans for reaction to sensor information.

**a) Random Forest**

Random forest is a powerful machine learning technique used for both regression and classification. An ensemble learning technique is used to merge multiple decision trees into a powerful classifier. We shall go into great detail about random forest in this response, covering its formulas and algorithm.

Equations:

Random forest uses decision trees as building blocks. The output of a decision tree is a binary classification or a numerical value, depending on the problem type. The output of a decision tree can be represented mathematically as follows:

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

$y = f(x)$

Where:

- $x$ is the input data
- $f$ is the decision function that maps input data to output data
- $y$ is the output data

Several decision trees are used by Random Forest to produce a more powerful classifier. The following is a mathematical representation of a random forest's output:

$y = 1/N * \sum f_i(x)$

Where:

- $N$ is the number of decision trees in the random forest
- $f_i$ is the decision function of the i-th decision tree
- $y$ is the output data

Algorithm:

The following is the algorithm for random forest:

1. Collect and preprocess data: Collect the data and preprocess it by handling missing values and outliers, scaling the data, and splitting it into training and testing sets.
2. Build decision trees: Build multiple decision trees using bootstrapped samples of the training data and a subset of the features at each node of the tree.
3. Compute the ensemble output: Compute the output of the random forest by taking the average of the output of all decision trees.
4. Make predictions: Use the trained model to make predictions on new data.

The fundamental idea behind random forests is to use several decision trees to reduce overfitting and raise the accuracy of the model. Every decision tree in the random forest is built using a random subset of the attributes and a bootstrapped sample of the training data. This process, referred to as bagging, helps reduce the variance of the model. At each node, a random subset of features is chosen in order to increase the diversity of the decision trees in the forest.

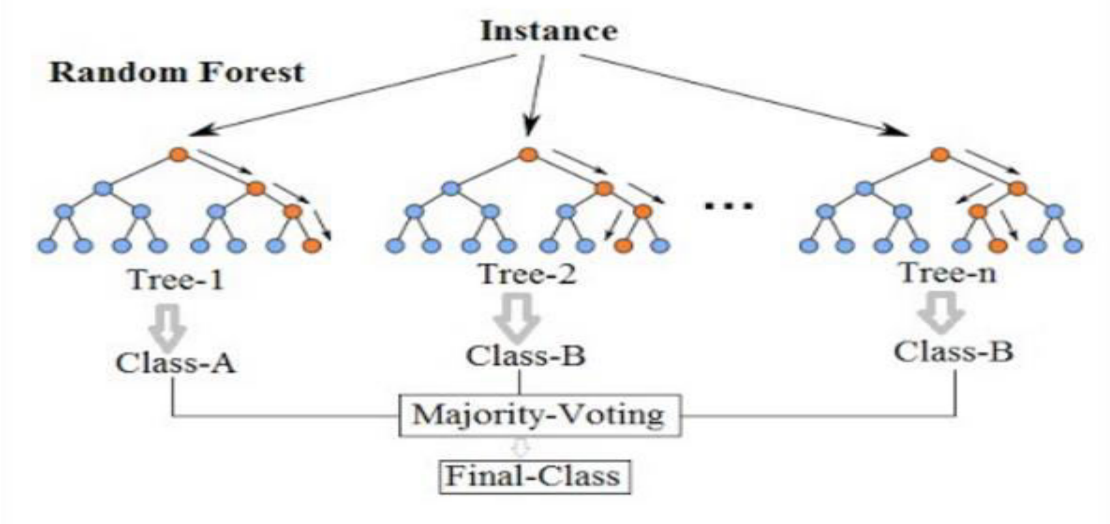


Figure 1: Random forest

The average of the outcomes from each decision tree in the analysis is used to determine the random forest's output. This procedure, which lessens the bias the model displays, is referred to as "ensemble learning." One technique for optimizing hyperparameters, such the quantity of decision trees in a random forest, is cross-validation.

The efficacy of the random forest can be assessed using a variety of measures, such as accuracy, precision, recall, F1 score, and mean squared error, depending on the type of problem being handled. The random forest may also provide information on the significance of each characteristic in the data by computing the permutation importance or the Gini significance of each feature. The random forest can be used to gather this data.

To put it briefly, the random forest approach is a powerful machine learning tool that can be applied to regression and classification tasks. It achieves this by reducing overfitting and enhancing the model's accuracy through the use of several distinct decision trees. The initial phase in the procedure is to build decision trees using bootstrapped samples of the training data and a random subset of the characteristics at each node of the tree. Making predictions using newly collected data is the final phase. The ensemble output is then determined by averaging the results of each decision tree. A range of metrics can be used to track the random forest's performance, and it can also provide details on the importance of each feature in the data. In statistical analysis and machine learning, random forests are frequently utilized.

## 4. Experimental Results

The experimental findings that were carried out in order to verify the suggested model are presented in this section.

### 4.1 AI assisted Crop Selection

Figure 2 shows the nitrogen for crops

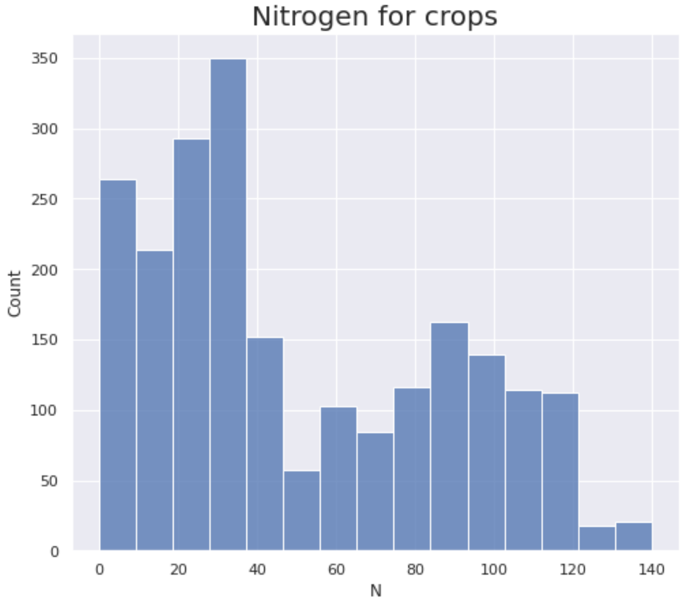


Figure 2: Nitrogen for crops

Figure 3 shows the Potassium for crops

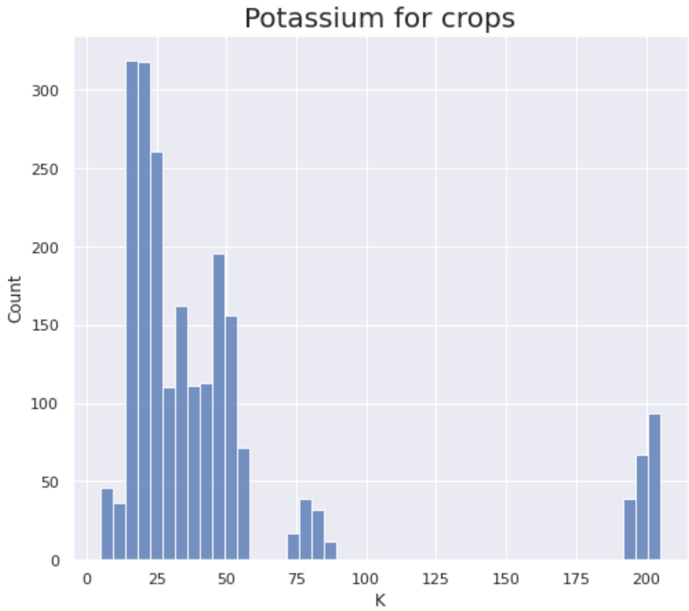


Figure 3: Potassium for crops

Figure 4 shows the Phosphorus for crops

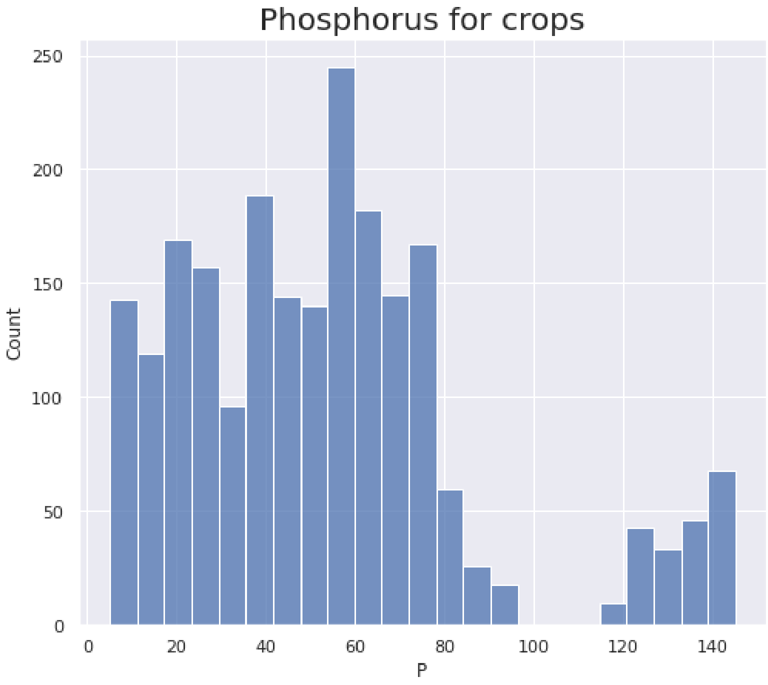


Figure 4: Phosphorus for crops

Figure 5 shows the PH for crops

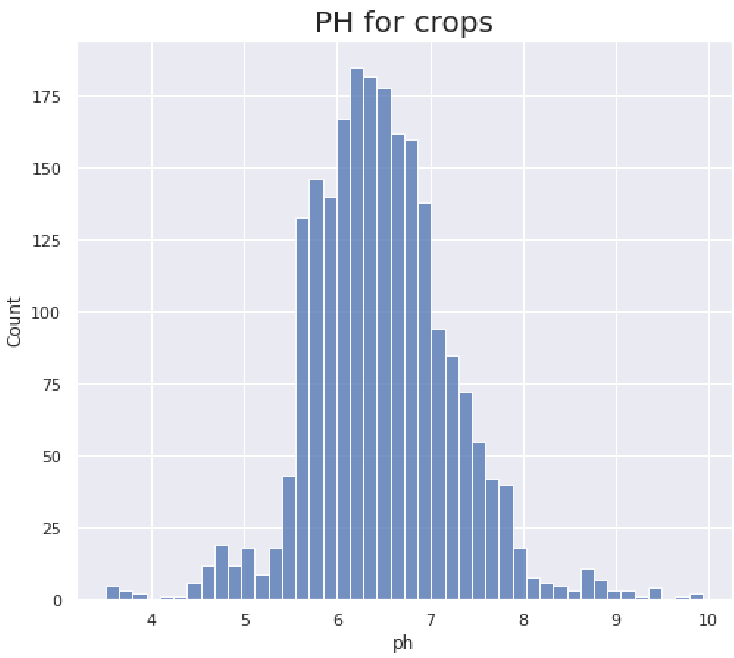


Figure 5: PH for crops

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Figure 6 shows the rainfall for crops

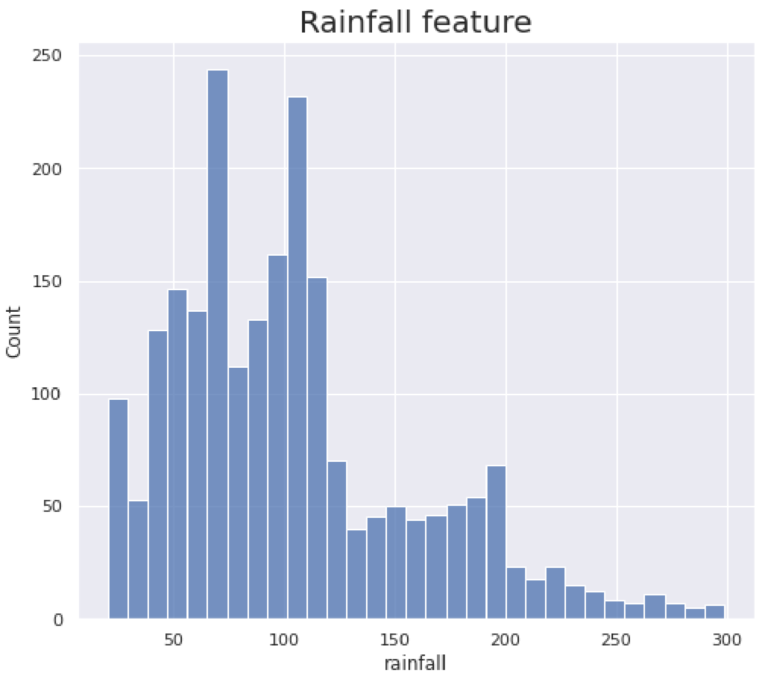


Figure 6: Rainfall for crops

Table 1 shows the precision, recall and f1-score of Random Forest Classifier model

Table 1: Random Forest Classifier model

| | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Apple | 1.00 | 1.00 | 1.00 |
| Banana | 1.00 | 1.00 | 1.00 |
| Blackgram | 1.00 | 1.00 | 1.00 |
| Chickpea | 1.00 | 1.00 | 1.00 |
| Coconut | 1.00 | 1.00 | 1.00 |
| Coffee | 1.00 | 1.00 | 1.00 |
| Cotton | 1.00 | 1.00 | 1.00 |
| Grapes | 1.00 | 1.00 | 1.00 |
| Jute | 0.92 | 1.00 | 0.96 |
| Kidneybeans | 1.00 | 1.00 | 1.00 |
| Lentil | 1.00 | 0.94 | 0.97 |
| Maize | 1.00 | 1.00 | 1.00 |
| Mango | 1.00 | 1.00 | 1.00 |
| Mothbeans | 0.95 | 1.00 | 0.97 |
| Mungbean | 1.00 | 1.00 | 1.00 |
| Muskmelon | 1.00 | 1.00 | 1.00 |
| Orange | 1.00 | 1.00 | 1.00 |

| | | | |
|---|---|---|---|
| Papaya | 1.00 | 1.00 | 1.00 |
| Pegionpeas | 1.00 | 1.00 | 1.00 |
| Pomegranate | 1.00 | 1.00 | 1.00 |
| Rice | 1.00 | 0.91 | 0.95 |
| Watermelon | 1.00 | 1.00 | 1.00 |

The evaluation metrics for a classification model's performance on distinct classes—like different kinds of crops—are shown in the table. The model performs well overall in classifying these classes, with high accuracy and identification for the majority and minor deviations for a few specific classes. The metrics, which measure the quality of the model's predictions, are Precision, Recall, and F1-score. Across most classes, the model achieves perfect scores with precision, recall, and F1-score all set at 1.00, indicating accurate positive predictions, complete identification of instances, and a balanced combination of precision and recall.

Table 2: Accuracy

| **Model name** | **Accuracy** |
|---|---|
| Logistic Regression | 0.97 |
| Multi-layer Perceptron | 0.14 |
| Random Forest Classifier | 0.99 |

The table compares how well several machine learning models perform on a given problem, most likely a classification test. Here, the main assessment metric is "Accuracy," which quantifies the frequency with which the model's predictions coincide with the actual results.

- **Logistic Regression:** With an accuracy of 0.97, this model was able to accurately predict 97% of the dataset's cases.
- **Multi-layer Perceptron:** This model did not perform well, correctly predicting only 14% of cases, as seen by its accuracy of 0.14. This can point to problems with the model's training or configuration.
- **Random Forest Classifier:** With an accuracy of 0.99, this model demonstrated remarkable performance, accurately predicting 99% of the cases. An ensemble model called Random Forest aggregates the forecasts of several decision trees in order to increase accuracy.

### 4.2 Smart Irrigation

Figure 7 shows the moisture data. The x-axis shows the moisture values. Y values shows the pump on off value in terms of 0 and 1.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

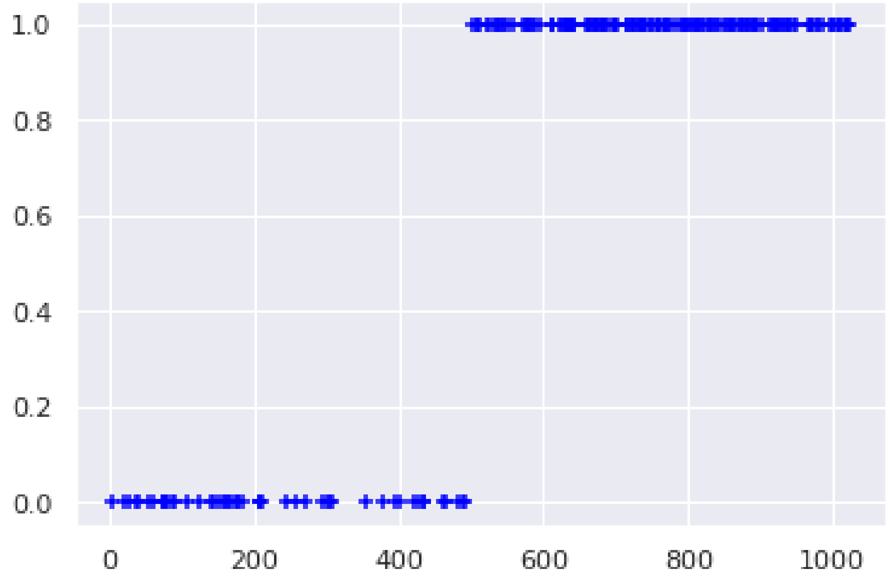


Figure 7: Moisture data

Figure 8 shows the temperature data. The x-axis shows the temperature values. Y values shows the pump on off value in terms of 0 and 1.

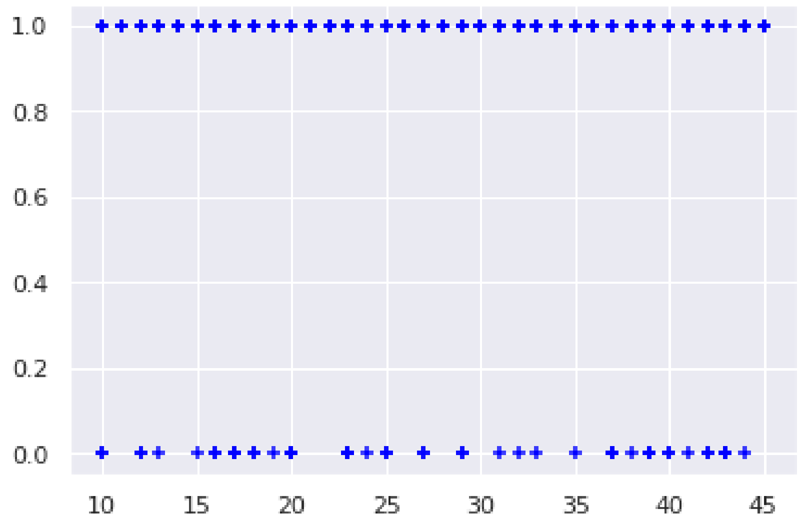


Figure 8: Temperature data

Figure 9 shows the moisture and temperature data plotted combined in one 3d plot with x axis as moisture, y axis as temperature and z axis as pump on and off.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

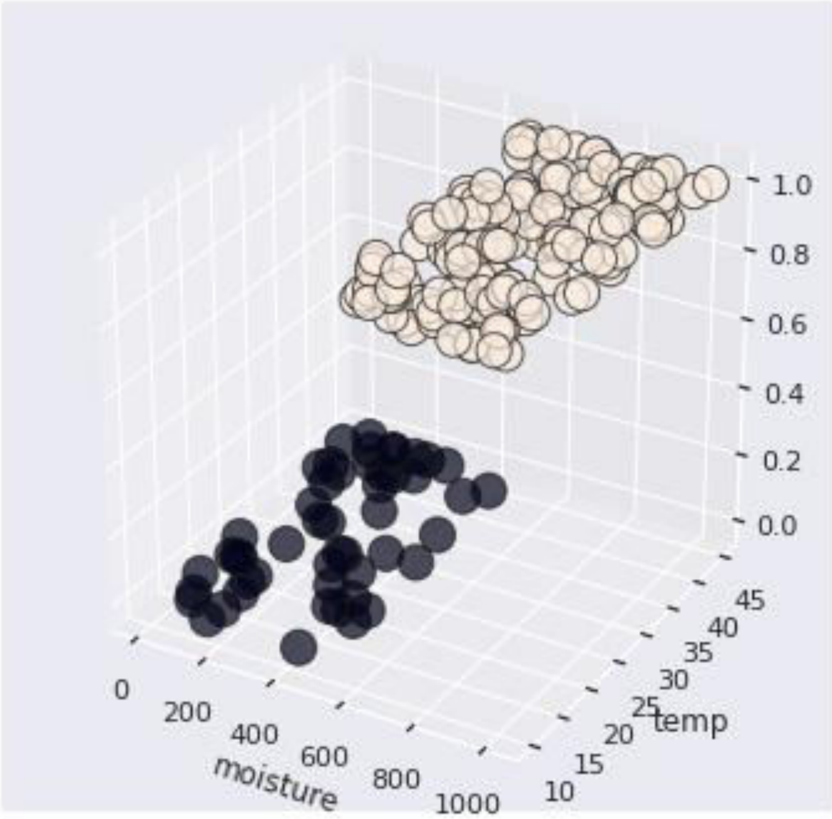


Figure 9: Moisture and temperature data

The accuracy metric shows the models' capacity to accurately predict outcomes in a classification test, and table 3 shows the accuracy performance of three machine learning models: "Logistic Regression," "Multi-layer Perceptron," and "Random Forest Classifier." The accuracy of the "Multi-layer Perceptron" and "Logistic Regression" models was 0.95, meaning that 95% of the time, the predictions were correct. Interestingly, the "Random Forest Classifier" model scored a perfect 1.00 for accuracy, meaning that all of the dataset's cases had accurate predictions.

Table 3: Accuracy

| **Model name** | **Accuracy** |
|---|---|
| Logistic Regression | 0.95 |
| Multi-layer Perceptron | 0.95 |
| Random Forest Classifier | 1.00 |

## 5. Conclusion

Crop determination in view of machine learning is likewise worthwhile for the climate. Ranchers might reduce their utilization of pesticides, composts, and different synthetics by picking crops that are viable with the neighborhood environment. This will work on the biological system. Moreover, ranchers can ration water assets by picking less water-escalated crops, which is significant in locales encountering water shortage or dry season. Improved viability is an extra benefit of machine learning driven crop choice. machine learning calculations can figure out which yields are probably going to prosper in a particular spot and when they ought to be planted by assessing information on weather conditions and soil conditions. As well as lessening the opportunity of harvest disappointment attributable to climate related causes, this outcomes in a more productive utilization of assets like work, manure, and water. machine learning based crop determination can likewise help ranchers in decreasing the dangers associated with environmental change. Ranchers might pick crops that are more impervious to outrageous climate occasions like intensity waves, floods, and dry spells by utilizing machine learning calculations that investigate authentic climate information and figure future weather conditions patterns. By doing this, ranchers will be more prepared to deal with the difficulties presented by a changing climate and the probability of harvest disappointment will be diminished.

**References**

[1] Ukhurebor, Kingsley Eghonghon, Charles Oluwaseun Adetunji, Olaniyan T. Olugbemi, W. Nwankwo, Akinola Samson Olayinka, C. Umezuruike, and Daniel Ingo Hefft. "Precision agriculture: Weather forecasting for future farming." In *AI, Edge and IoT-based Smart Agriculture*, pp. 101-121. Academic Press, 2022.

[2] Raj, E. Fantin Irudaya, M. Appadurai, and K. Athiappan. "Precision farming in modern agriculture." In *Smart Agriculture Automation Using Advanced Technologies: Data Analytics and Machine Learning, Cloud Architecture, Automation and IoT*, pp. 61-87. Singapore: Springer Singapore, 2022.

[3] Bwambale, Erion, Felix K. Abagale, and Geophrey K. Anornu. "Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review." *Agricultural Water Management* 260 (2022): 107324.

[4] Zinkernagel, Jana, Jose F. Maestre-Valero, Sogol Y. Seresti, and Diego S. Intrigliolo. "New technologies and practical approaches to improve irrigation management of open field vegetable crops." *Agricultural Water Management* 242 (2020): 106404.

[5] Dakir, Asmae, Fatimazahra Barramou, and Omar Bachir Alami. "Opportunities for artificial intelligence in precision agriculture using satellite remote sensing." *Geospatial Intelligence: Applications and Future Trends* (2022): 107-117.

[6] Rezk, Nermeen Gamal, Ezz El-Din Hemdan, Abdel-Fattah Attia, Ayman El-Sayed, and Mohamed A. El-Rashidy. "An efficient IoT based smart farming system using machine learning algorithms." *Multimedia Tools and Applications* 80 (2021): 773-797.

[7] Meshram, Vishal, Kailas Patil, Vidula Meshram, Dinesh Hanchate, and S. D. Ramkteke. "Machine learning in agriculture domain: A state-of-art survey." *Artificial Intelligence in the Life Sciences* 1 (2021): 100010.

[8] Tong, Hao, and Zoran Nikoloski. "Machine learning approaches for crop improvement: Leveraging phenotypic and genotypic big data." *Journal of plant physiology* 257 (2021): 153354.

[9] Paudel, Dilli, Hendrik Boogaard, Allard de Wit, Sander Janssen, Sjoukje Osinga, Christos Pylianidis, and Ioannis N. Athanasiadis. "Machine learning for large-scale crop yield forecasting." *Agricultural Systems* 187 (2021): 103016.

[10] Deepa, Natarajan, and K. Ganesan. "Hybrid rough fuzzy soft classifier based multi-class classification model for agriculture crop selection." *Soft computing* 23 (2019): 10793-10809.

[11] Maponya, Mmamokoma Grace, Adriaan Van Niekerk, and Zama Eric Mashimbye. "Pre-harvest classification of crop types uses a Sentinel-2 time-series and machine learning." *Computers and electronics in agriculture* 169 (2020): 105164.

[12] Seetharaman, K. "Real-time automatic detection and classification of groundnut leaf disease using hybrid machine learning techniques." *Multimedia Tools and Applications* 82, no. 2 (2023): 1935-1963.

[13] Filippi, Patrick, Edward J. Jones, Niranjan S. Wimalathunge, Pallegedara DSN Somarathna, Liana E. Pozza, Sabastine U. Ugbaje, Thomas G. Jephcott, Stacey E. Paterson, Brett M. Whelan, and Thomas FA Bishop. "An approach to forecast grain crop yield using multi-layered, multi-farm data sets and machine learning." *Precision Agriculture* 20 (2019): 1015-1029.

[14] Elavarasan, Dhivya, and PM Durai Raj Vincent. "A reinforced random forest model for enhanced crop yield prediction by integrating agrarian parameters." *Journal of Ambient Intelligence and Humanized Computing* (2021): 1-14.

[15] Ponnusamy, Vijayakumar, and Sowmya Natarajan. "Precision agriculture using advanced technology of IoT, unmanned aerial vehicle, augmented reality, and machine learning." *Smart Sensors for Industrial Internet of Things: Challenges, Solutions and Applications* (2021): 207-229.