

Agricultural Machine learning platform: Enhancing crop suggestion and crop yield estimates

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Submitted on: 12-Aug-2024, Accepted and Published on: 20-Nov-2024

Article

ABSTRACT

Crop analysis and prediction is a rapidly growing field that plays important role to improve farming methods. It provides farmers with the knowledge and skills to select the best crops for their specific climate and land. Machine learning techniques can be very helpful in automatically recommending crops and identifying pests and diseases, allowing farmers to maximize crop yield while simultaneously preserving soil fertility and replenishing important nutrients. Using seven different machine-learning algorithms, the crop recommendation and crop yield prediction is show in this paper. The proposed system uses several features, including soil composition and climate data, to accurately predict which crops would be most suitable for a given location. Crop recommendation could be revolutionized by this system, which would help all farmers by increasing crop yields, sustainability, and overall profitability. Through extensive evaluation of an extensive historical data set, we have achieved near-perfect accuracy by training and testing models with various configurations of machine learning algorithms. We show that accuracy in this paper is 99.54% being the highest accuracy ever attained.

Keywords: Machine Learning, Prediction, Data Analysis, Big Data, Agriculture, Crop, Food, Environmental Factors, Agricultural Productivity

INTRODUCTION

As a significant industry in the world, agriculture demands that farmers grow crops that are both sustainable and profitable. Crop yield can be greatly impacted by improper crop selection, which can lower productivity and possibly result in financial losses for farmers.¹ The selected crops might not be able to grow well and produce as much as they could. when farmers overlook important factors like soil conditions, market demand, and climate suitability. Inadequate climate adaptation in inappropriate crops can lead to stunted growth, heightened susceptibility to pests and diseases, and a decrease in total yield. Furthermore, crops that don't match market

demand might have trouble finding buyers or bringing in a fair price, which would hurt farmers' bottom lines even more. Farmers may effectively handle these challenges and make educated decisions that enhance crop output and maintain agricultural sustainability over time by utilizing machine learning-based crop recommendation systems.

Machine learning and agricultural data convergence will transform farmers' understanding of their practices and how they optimize them.² With an increasing amount of data coming from satellites, sensors, weather stations, and agricultural equipment, machine learning algorithms are better equipped to sift through massive quantities of data and take out useful hints. These algorithms enable the discovery of intricate correlations, patterns, and predictive models. Farmers can increasingly use agricultural data and machine learning techniques to make data-driven decisions about anything, including pest control, yield prediction, crop selection, and irrigation management. Through increased productivity and profitability, farmers are eventually able to

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Cite as: J. Integr. Sci. Technol., 2025, 13(1), 1017.

URN:NBN:sciencein.jist.2025.v13.1017

DOI:10.62110/sciencein.jist.2025.v13.1017

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implement sustainable practices, resource optimization, and increased efficiency through this integration.

A range of data, including soil, weather, and market data, can be analyzed by crop recommendation systems. Machine learning algorithms that determine which crops have the best chance of succeeding in a certain region can be trained using this data. Crop recommendation systems have the ability to educate farmers on the optimal methods for cultivating particular crops.

Machine learning-based crop recommendation systems have the potential to increase agricultural sustainability and output.

With the aid of crop recommendation systems, farmers can select more productive crops while utilizing fewer resources.

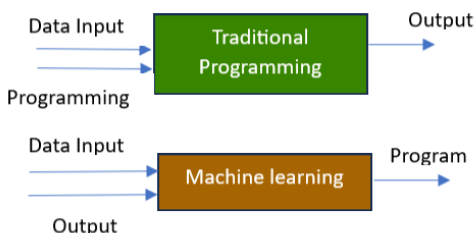


Figure 1: Programming conventions versus machine learning

Crop recommendation systems can also increase agriculture's ability to adapt to climate change.¹ Furthermore, machine learning is capable of help with a number of other agricultural problems, such as forecasting crop yield, spotting pests and illnesses, increasing crop productivity, lowering the need for fertilizers and pesticides, managing soil, and so forth.

The world's population primarily obtains its food and fiber from crops. Consequently, raising the yield of high-quality crops is crucial. Crop yields and profitability can be greatly impacted by the crops that are planted. Given the location, the crop that will succeed is hard to anticipate because of climate shift as well as additional environmental factors.

In this paper, we recommend crops to farmers using machine learning. Gather and preprocess the dataset first. Next, we use features like soil type and content, pH level, temperature, humidity, and rainfall to train and test the models. In order to determine whether combining different features improves the model's performance. We also experimented with feature engineering ideas and used the results to create additional features inside the same dataset. We address these general challenges in detail because they are relevant to machine learning in the context of agriculture. Finally, we offer the readers a few intriguing concepts to consider.

BACKGROUND SURVEY

Machine Learning

Thanks to machine learning, computers can now learn without explicit programming. Stated differently, machine learning is the process of turning data or objects into numerical values and then looking for patterns within those values. The discovered patterns help predict the outcomes for new data points. The main difference what separates machine learning from traditional programming is

depicted in Figure 1. There are two different techniques to issue solving: classical programming and machine learning. The classic approach to programming is creating code that specifies how a particular problem should be solved by the software. However, machine learning entails using data to train a model so that it can independently solve problems. Based on how computers learn, machine learning algorithms are generally divided into three groups.

Supervised Learning:

Labeled data is used to train models³ in machine learning under supervision. This indicates that the appropriate output has been appended to the data. The prototype then acquires the capacity to predict outcomes for recently gathered, unlabeled data. Numerous supervised machine learning methods are available, including neural networks, logistic regression, decision trees, and support vector machines.

Unsupervised Learning:

Using an unsupervised learning approach to machine learning, the model is trained on an unlabeled database.⁴

Reinforcement Learning:

One kind of machine learning that enables an agent to learn is called reinforcement learning (RL) environmental behavior by making mistakes first.³ When an agent takes activities that result in desired consequences, they are rewarded; when they do acts that result in unwanted outcomes, they are punished. The agent gets the ability to operate in a way that optimizes its gains over time. Reinforcement learning includes techniques such as policy gradients, q-learning, and actor-critic algorithms.

Machine learning algorithms used

In this survey, we are only emphasizing the following machine learning algorithms because we used them in our investigation, despite the fact that many other algorithms are also frequently used.

Logistics Regression:

A statistical technique used to determine the likelihood of an event occurring is called logistic regression.⁴ This type of regression analysis is used to model the relationship between one or more independent variables and a categorical dependent variable.

Decision Tree

A decision tree is a kind of supervised learning technique, that expresses the relationship between the input and output data using a structure resembling a tree. Nodes and branches make up a decision tree. Nodes represent decisions, and branches show potential results.

Random Forest

An ensemble is called a random forest learning system composed of many decision trees.⁵ To construct random forests, Different subsets of the training data are used to train multiple decision trees. One arbitrary subset of the attributes is used for training for each decision tree. Every To make a prediction, a decision tree in the random forest generates one. The ultimate forecast is determined by taking into account the predictions given by the majority of each decision tree. Random forests are frequently employed in applications involving regression and classification.

K-nearest Neighbour

As a supervised learning algorithm, the k-nearest neighbors (KNN) algorithm technique.⁶ In order to predict the label of a new input instance, KNN first determines which k neighbors the training set's most comparable to the input instance. By comparing the labels of the k closest neighbors to the new input instance, this is accomplished. Regression and classification problems are both solvable with this approach.

Naive-bayes

The Bayes theorem is used by the supervised learning method known as the naive Bayes algorithm.⁷ This versatile, user-friendly algorithm can be used for a variety of applications, such as spam filtering, medical diagnostics, and text classification. The naive Bayes algorithm functions based on the presumption that a feature's existence is independent of the presence of any other feature in a class. This might not always be the case. That explains the term "naive". Nonetheless, it's frequently a good approximation, which makes the algorithm easier to understand and train. The Naive Bayes algorithm determines the probability for each class before classifying an object. The likelihood of each feature being assigned to each class is then approximated. The object is assigned to the class that has the highest likelihood.

SVM

Support vector machines (SVMs) are algorithms used in supervised learning.⁸ It is necessary to identify the hyperplane that divides the data into two classes basis of support vector machines (SVMs). Based on optimizing The hyperplane is selected based on the separation between it and the nearest data points on both sides. This method can be applied to tasks involving regression as well as classification.

Neural Network

The human brain serves as the model for a neural network.⁹ It is made up of interconnected neurons, sometimes known as edges or connections, which make up a network of nodes. Multiple layers of nodes comprise neural networks. The input layer is at the top of the neuronal layers, whereas the output layer is at the bottom. Hidden layers are the layers that lie between. In a neural network, every neuron has several inputs and one output. The outputs of the neurons in the layer above are the inputs of a neuron. The function that determines a neuron's output is called an activation function. The input of a neuron is converted into an output via the non-linear activation function. The sigmoid function is the most often utilized activation function. But we might provide a personalized activation function if that's what you require.

Current Crop Recommendation Research

A systematic literature review on the use of deep learning (DL) techniques for predicting crop yield, a key area in precision agriculture aimed at enhancing productivity and optimizing resource allocation Oikonomidis et al.¹⁰ addresses the issue of crop selection for agricultural fields, proposing an intelligent crop recommendation system that leverages machine learning (ML) techniques Chakraborty et al.¹¹ explores the development of an intelligent crop recommendation system, named Agro consultant, that utilizes machine learning (ML) algorithms to assist farmers in selecting the most suitable crops based on environmental and soil

characteristics. Desai et al.¹¹ provided a practical and farmer-friendly yield prediction system. The prototype using a majority voting technique is proposed by researchers¹² where ANN and SVM are used to select a crop. Pudumalar et al.¹³ described a similar method that applies machine learning to information collected from a Tamil Nadu, India, district; the accuracy of the models is not discussed in the paper or provide details on the data used. The majority of these applications are covered in "Machine Learning in Agriculture" by Konstantinos G. Liakos et al.¹⁴ There is a greater body of agricultural literature that indirectly connects crop recommendation. For instance, sensors and the Internet of Things are largely discussed in Ayaz Muhammad et al.'s study¹⁵ in relation to the gathering of agricultural information. Some other categories of literature on crops address crop yield prediction. In this paper present crop recommendation, according. The article by Chaudhary R.R et al.¹⁶ critically analyzes the application of machine learning (ML) techniques in crop management, focusing on how these technologies can be leveraged for smart and precise farming. The authors explore various ML algorithms and their effectiveness in optimizing agricultural practices, such as crop prediction, disease detection, and yield estimation. They emphasize the role of ML in improving decision-making processes, thereby enhancing productivity and sustainability in farming. The study also discusses the challenges and future directions for integrating ML into agriculture, highlighting the need for more research and development to fully realize its potential in precision farming.

Data Description and methodology

Data Description

There is a greater body of agricultural literature that indirectly connects crop recommendation. For instance, sensors and the Internet of Things are largely discussed in Ayaz Muhammad et al.'s study¹⁵ in relation to the gathering of agricultural information. Some other categories of literature pertaining to crops address crop yield prediction. The specific challenging subpublications mentioned above have existed for four to five years. Aside from that, we are preparing an existing Kaggle dataset¹⁷ for the model we use. Table I presents the primary characteristics of the information, while Table II shows a selection of the data for crop suggestions. Table IV displays a sample of the crop yield data, whereas Table III shows the crop yield data description. Figure 3 provides a visual representation of the attributes along with their quantity. Figure 2 displays the feature pair plot that was employed. One sort of statistical graph is a pair plot in which the interactions among several characteristics are shown as a matrix inside a dataset, and each row and column of the graph represents a distinct variable. Plots in the matrix's off-diagonal region display the relationships between pairs of variables, while plots on the diagonal of the matrix display the distribution of each variable. The creator of this dataset was adding data sets related to fertilizer, rainfall, and climate for India. Table III contains the data that we employed, and the data were given a total of 22 unique labels.

These labels come from a database that held over 100,000 records; due to the fact that a given configuration can only support one decent crop, the records were reduced to roughly 2.2k.

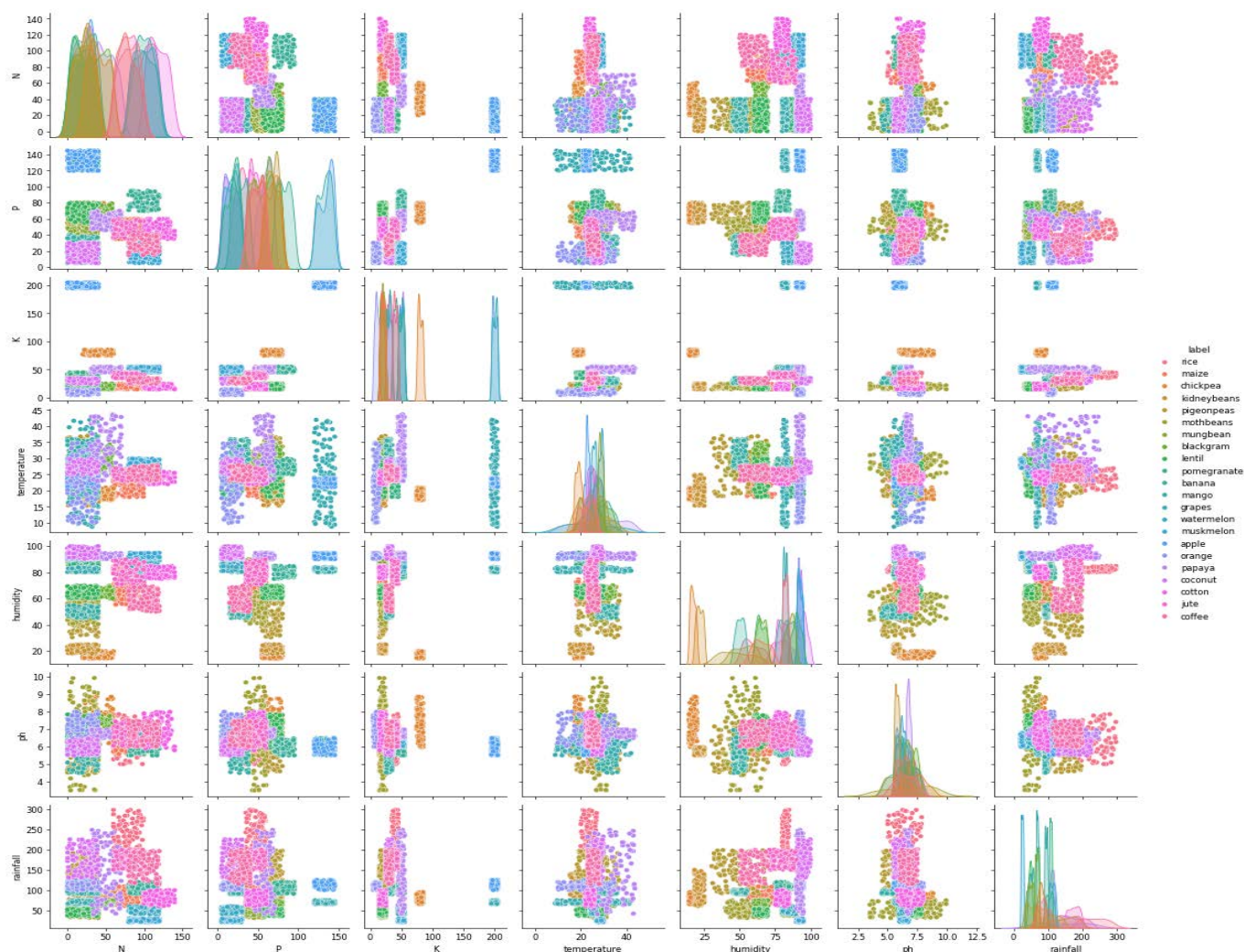


Figure 2: Pair Plotting of All Data

Table I: Main Features

Index	Feature_name	Feature_description
1	Nitrogen(N)	Nitrogen is largely responsible for the growth of leaves on the plant
2	Phosphorus(P)	Phosphorus is largely responsible for root growth and flower and fruit development
3	Potassium(K)	Potassium is a nutrient that helps the overall functions of the plant perform correctly
4	Humidity	Relative humidity in %
5	Temperature	Temperature in degree celsius
6	pH	pH value of the soil
7	Rainfall	Rainfall in mm

Table II Sample Dataset for Crop recommendation

S.no	N	P	K	Temperature	Humidity	PH	Rainfall	classes
1	65	37	40	23.35905428	83.59512273	5.333322606	188.413665	rice
2	71	54	16	22.61359953	63.69070564	5.749914421	87.75953857	maize
3	40	72	77	17.02498456	16.98861173	7.485996067	88.55123143	chickpea
4	13	60	25	17.13692774	20.59541693	5.685972	128.256862	kidneybeans
5	22	60	24	18.78226261	20.24768	5.630664753	104.2571	kidneybeans
6	10	79	18	21.0643684	55.46985938	5.6247313379	184.6277	Pigeonbeans

Table III: Data Description for Crop_yield

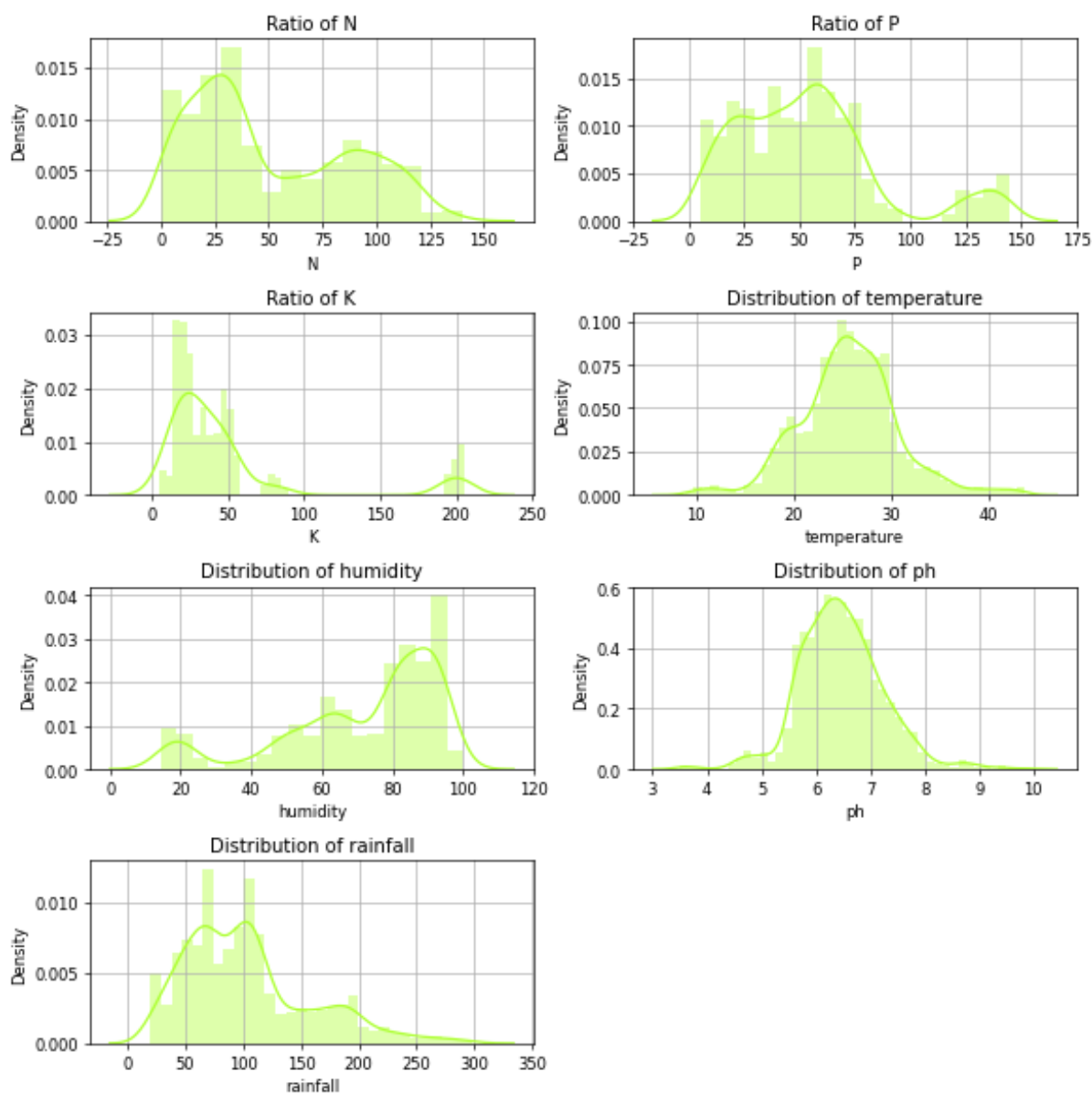
Index	Feature_name	Feature_description
1	Crop	The crop's name
2	Crop year	The year that the crop was planted
3	Season	Particular season
4	State	the state in India where the crop was grown
5	Area	The entire land area measured in hectares
6	Annual Rainfall	The yearly precipitation in millimeters that the crop-growing region receives
7	Fertilizers	The total kilograms of fertilizer applied to the crop
8	Pesticides	The total kilograms of pesticide applied to the crop
9	Production	The amount of crops produced (measured in metric tons)

Table IV: Few data for crop yield prediction

S. N o.	Crop	Year	Season	State	Area	Production	Annual Rainfall	Fertilizers	Pesticide	Yield
1	Area cnut	1997	Whole year	Assam	73814	56708	2051.4	7024878	22882	.796087
2	Arhar	1997	Kharif	Assam	6637	4685	2051.4	631643	2057	.710435
3	Castor seed	1997	Kharif	Assam	796	22	2051.4	75755	246	.238333
4	Cocunut	1997	Whole Year	Assam	19656	126905000	2051.4	1870661	6093	.5238051
5	Cotton	1997	Kharif	Assam	1739	794	2051.4	165500	539	.420909

Table V: Different labels of dataset

Index	Label_name	Index	Label_name
1	rice	13	Mango
2	Maize	14	Grapes
3	Coffee	15	Apple
4	Pigeonbeans	16	orange
5	chickpea	17	Papaya
6	muskmelon	18	Coconut
7	watermelon	19	cotton
8	Blackgram	20	Jute
9	Mothbeans	21	kidneybeans
10	Mongbeans	22	Pomegranate
11	lentil		
12	Banana		

**Figure 3:** Feature Graphs

METHODOLOGY

This section offers a pictorial summary of the methodology we utilized for instruction different models, as shown in Figure 4. First, we used every chosen machine learning algorithm listed in Section II to repeat each of the ensuing steps.

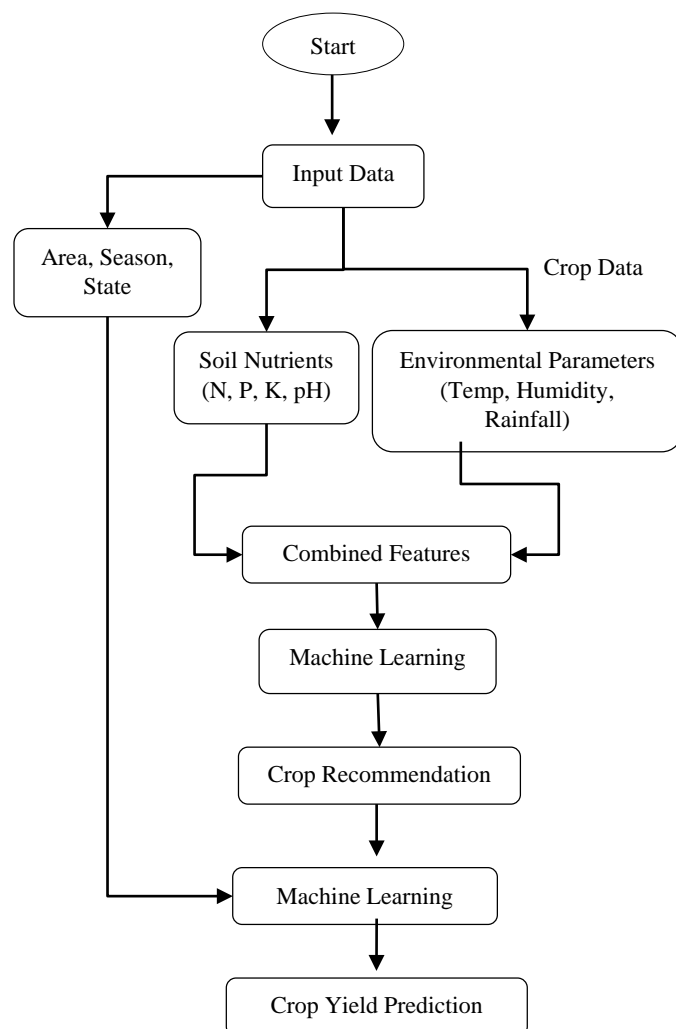


Figure 4. Overview of the Methodology

Input data: Because a model's accuracy is greatly influenced by both the quantity and quality of data, we made sure the data was appropriately labeled and classified. Figure 4 shows how a combination of soil and environmental factors affect the system's input. An illustration of the raw data we used for model testing and training can be found in Table II.

Preprocessing: We prepared the data for your machine learning algorithm to understand by cleaning it up and eliminating anomalies. First, we made sure there were no abnormalities by taking out The steps in the feature engineering process include removing all null and duplicate records, separating features from the label column, creating new features from preexisting features, and characterizing and plotting all of the data.

Choose a machine Learning model: We selected to employ one of the seven algorithms. The preprocessing and testing were

repeated and validation phases for each chosen algorithm in order to fine-tune the model.

Train and testing the accuracy of model: This is the stage in which the data prepared in the "Preprocessing" step is used to teach the machine learning algorithm. We compare the developed model's accuracy with the test data. The accuracy of the model's cross-validation was also evaluated. If the accuracy is subpar, should the, we go back to the "Model Configuration" step and repeat the process. We tried the feature engineering method in a few different cases. Assume that at this point, the model performs well and has good accuracy. If so, we go back to selecting a fresh algorithm step and carry out the same process once more using a different sophisticated machine learning algorithm.

Crop recommendation: After training and testing the accuracy of model our model give the crop recommendation on the basis of some feature like Soil Nutrients (N,P,K, pH), Environmental Parameters (Temp, Humidity, Rainfall).

Crop yield prediction: After crop recommendation our model predict the crop yield on the basis some feature like Area, Season, State.

C) Experimentation

To create a model using a different algorithm, we employed several classifier machine learning algorithms. This section discusses a few variations.

Table VI: Primary used classifier for Crop recommendation

Classifier	Machine learning model
Support vector machine	()
Decision Tree classifier	()
Random forest classifier	()
Naïve bayes	()
Logistic Regression	()

We used entropy and Gini, two impurity measures commonly used in decision trees, for the decision tree algorithm. Max depth was an additional parameter we employed in the decision tree. We used kernel configuration for SVM. The support-vector machine (SVM) is the most well-known member of the class of pattern analysis algorithms known as kernel machines regarding the Random forest classifier, we used the value of `n_estimator` which determine the number of tree to be used in forest.

Table VII: Primary used model for Crop Yield prediction

S. No.	Machine learning model
1	Linear Regression()
2	RandomForestRegressor()
3	XGBRegressor ()
4	Decisiontreeregressor()

Regarding the linear regression, By fitting a linear equation to observed data, the supervised machine learning algorithm known as linear regression establishes the linear relationship between the dependent variable and one or more independent features.

A meta estimator called a random forest uses averaging to control over-fitting and improve prediction accuracy. It fits several decision tree regressors to various dataset subsamples. Forest trees utilize the ideal split strategy.

A useful gradient boosting implementation for regression predictive modeling is called XGBoost. XGBoost regression model with repeated k-fold cross-validation, a best practice method.

Decision tree regression produces meaningful continuous output by projecting future data through the observation of an object's features and the training of a model within the structure of a tree.

RESULT AND EVALUATION

In table VI and table VII show the result of our experiment for crop recommendation and crop Yield prediction respectively. After experimenting with various splits between the train and test data, we ultimately decided on 70% training data and 30% testing data. We achieved Decision tree accuracy is 90%, Gaussian NB accuracy is 99%, and support vector machine accuracy is 10.68%. 99.54% accuracy was attained in random forest and 95.23% in logistic regression.

Table VIII: Model Accuracy for Crop Recommendation

S.no	Model name	Accuracy
1	DecisionTreeClassifier	90.00%
2	GaussianNB	99.00%
3	SVM.SVC	10.68%
4	Logistic regression	95.23%
5	Random forest	99.54%

We observed the accuracy for support vector machine is very low and the highest accuracy is achieved by Random forest classifier is 99.54%. Thus, we selected the Crop recommendation model's random forest classifier.

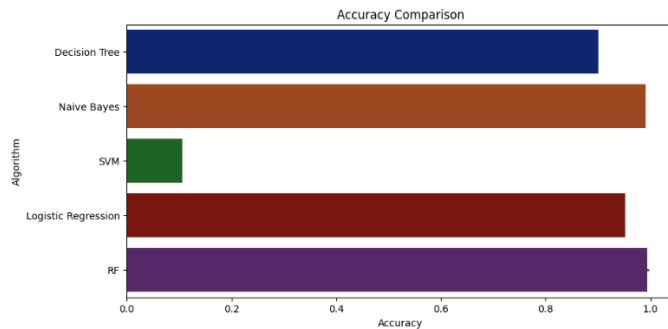


Figure 5. Accuracy comparison with different classifier

Table IX: Model Accuracy for Crop Yield prediction

S.no	Model name	Accuracy
1	Linear Regression()	38.71%
2	RandomForestRegressor()	99.447%
3	XGBRegressor ()	98.68%
4	Decisiontreeregressor()	99.429%

In the end, we settled on 30% of the data for testing and 70% for training. We were able to attain an accuracy of 38.71% for Linear Regression, 99.429% for Random Forest Regressor, 98.68% for XGB Regressor, and 99.447% for Decision Tree Regressor.

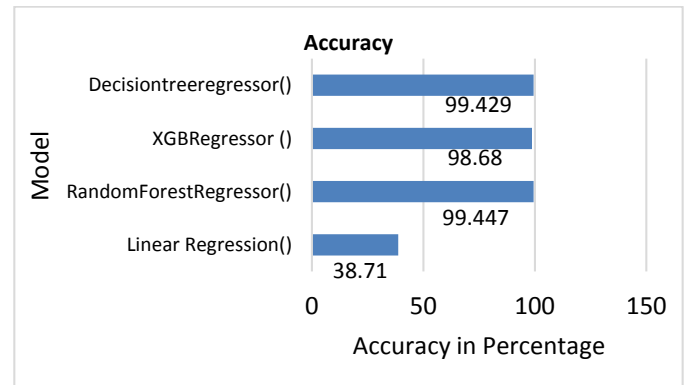


Figure 6. Accuracy comparison with different regression model

We observed the accuracy for Linear Regression is very low and the highest accuracy is achieved by Random forest regressor is 99.447%. So we decided the random forest regression for Crop yield prediction.¹⁸

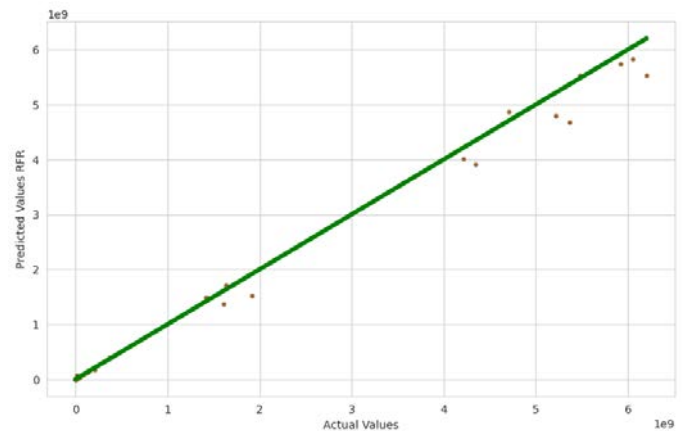


Figure 7. Show the predicted values vs Actual values

Testing

We will provide the temperature, humidity, pH, rainfall, and values for N, P, and K. Our model will then suggest a crop. It means which crop is best according to these values. We can show in figure 8 i provide the value of N=104, P = 18, K = 30, temperature = 23.603016, humidity = 60.3, ph = 6.7 and rainfall = 140.91 then the our model recommended the Coffee crop.

```
[ ] N = 104
    P = 18
    K = 30
    temperature = 23.603016
    humidity = 60.3
    ph = 6.7
    rainfall = 140.91

data = np.array([[N,P, K, temperature, humidity,ph, rainfall]])
prediction = RF.predict(data)
print(prediction)

['coffee']
```

Figure 8: Show the result of Crop recommendation


```
new_production = pd.DataFrame({'Crop': [11], 'Crop_Year': [1997], 'Season': [1], 'State': [2], 'Area': [1739.0 ], 'Annual_Rainfall': [2051.4],
predicted_production = model.predict(new_production)
print("Production:", predicted_production[0])
```

Production: 6625266.264174998

Figure 9: Show the result of Crop yield Prediction

As shown in figure 9 our model predict the crop yield on the basis of value Crop, Crop-year, state, area, annual rainfall, pesticides, fertilizers.

CONCLUSION

To sum up, this study has introduced crop recommendation models and crop yield prediction model that use a multiple sophisticated machine learning algorithms to predict which crops are best to grow and how much crop is grown in particular area. The method is adaptable and scalable to new data sets, geographical areas, and nations.

The agricultural industry will gain from this study's conclusions in several ways. Initially, the method can help farmers choose which crops to plant with more knowledge. Secondly, governments can use this method to create policies that help the agriculture industry. Thirdly, companies can use the technique to develop new goods and services that boost the agriculture sector; and Fourthly, it will contribute to the stability of agricultural product prices. When all is said and done, this research has greatly advanced the agricultural field. The approach is easy to use, scalable, and accurate. which makes it an invaluable resource for companies, governments, and farmers.

ACKNOWLEDGMENTS

Author acknowledge the support from ITM University for necessary research facilities.

CONFLICT OF INTEREST STATEMENT

Authors declare that there is no conflict of interest for this work.

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