IoT-Driven Enhanced Crop Recommendations with MachineLearning Algorithms

Naga Venkata Aswini Pavan Kumar Inguva[1] , Dr. Steven Brown[2]

Ph.d/ Doctoral in information technology,

Professor, Dept. School of Computer Information Sciences,

***Abstract*—**The Indian economy is heavily reliant on the agricultural sector. The farming industry has the potential to proliferate in the coming decades. 'The globe has to produce 70% more food in 2050 than 2006 in order to feed the expanding population of the Earth,' states the UN Food and Agriculture Organisation. Food consumption is increasing at a high pace parallel to the rise of the global population. Changes to farming practices are required to bring supply and demand into balance. Identification of suitable crops based on soil properties is a major problem that farmers face. Irregular and traditional soil testing methods further contribute to huge losses in the agriculture sector. Internet of Things (IoT) along with machine learning methodologies, will become one of the technological advances to solve this problem. This article proposes a new method “Enhanced Crop Recommendation System (ECRS)” for effective crop recommendation to the farmers based on soil properties using the Internet of Things and Machine learning technical advancements. In the first stage, The Internet of Things (IoT) with a variety of sensors and actuators has the potential to revolutionize contemporary farming. It provides insights and detailed data that help farmers figure out the optimal conditions for crops to grow. This way the farmers won’t waste soil and fertilizers, increase the quality and quantity of the crop, water conservation, remote monitoring, and contribute to the overall economic growth. In the second stage,different machine learning algorithms such as Random Forest, XGBoost, Gradient Boosted, Trees, Logistic Regression, Light GBM, Decision Tree, K Nearest Neighbors, and SVM are applied to give crop recommendations based on a dataset from the Kaggle database. This system helps the farmers choose ideal and appropriate crop varieties according to soil characteristics, and weather conditions with the help ofthe Enhanced Crop Recommendation System using LightGBM algorithm. Additionally, it also provides suitable crop recommendations via a user-friendly Mobile Application ‘Crop Recommender’ in the regional language (Telugu).Sensor data will be validated with soil testing laboratory values to know the accuracy of the IoT system.

Keywords—Farming, Soil properties, Internet of Things, Machine learning models, Crop recommendation

Introduction

Every country's economy relies on the agriculture industry. Traditional farming methods have long depended on farmers' knowledge and experiences to help them improve their methods [1]. Nevertheless, this approach isn't flawless and can lead to crop failure and financial losses. Countries are unable to fulfill their food demands due to conventional farming systems, which do not disclose accurate information on soil quality, specific water needs for each crop, and other important elements. Preserving soil today will yield better results in the future because it is essential to agricultural production. Optimizing the use of soil water and energy allows for the control of crop productivity while minimizing damage to plants, soil, and the environment. To maintain healthy soil and make farming more sustainable, it is essential to give farmers recommendations on the types and amounts of fertilizers to use based on the results of soil testing [2].

A farmer can increase food production by selecting crops that thrive in specific soil types and climates. Currently, farmers send soil samples to adjacent agricultural research centers for study [3]. It is also necessary to receive the test results from the same facility after one week. But it takes a long time and a lot of human effort to generate reports and give them to farmers.

Farmers rely on the soil science department for guidance in determining which crops will thrive in their specific soil type, given the local climate and other environmental factors. For a farmer, it will be a long process. The farmer must pay the soil testing laboratory for each sample. Some technologies, including the Internet of Things (IoT), can fix issues [4]. Through the use of several communication protocols, the Internet of Things (IoT) enables the expansion of the Internet to an enormous number of physical things. Using the characteristics of the soil and the current weather, the suggested method guides the farmer in choosing an appropriate crop. Sensors, a Raspberry Pi computer, cables, and modules for communication are all necessary pieces of hardware for this system to be put into action. The Raspberry Pi is the central processing unit (CPU) that all the sensors must have, and the data collected by the sensors can be saved to the Digital Ocean server in the cloud. Data analysis will be done using the sensor data, and the farmer will be given crop suggestions. This research will help the farmer choose the most suitable crop for the area's soil and weather. Smart farming refers to the practice of enhancing agricultural production efficiency and quality by the integration of contemporary technology into conventional farming practices. The quality of life for agricultural workers will also increase due to the reduction of heavy tasks.

Data and insights can be stored and organized using parsers, which are a set of criteria and judgments. Publicly accessible records, free of memorization or unnecessary ambiguity, are an excellent venue for displaying text. To accomplish desired goals, decision treesinclude a set of features that explain the relative importance of various requirements [5]. This research study's main objective is to develop a unique crop recommendation system that can assist farmers in making informed decisions on crop cultivation. The goal is to increase crop yields while decreasing expenses and boosting profitability.

This article is further organized as follows: The second section summarises the survey carried out. The proposed research methodologyis described in Section III. Section IV describes experimental findings and performance analysis. The conclusion is detailed under Section V.

II. Literature Review

AMNN Senevirathna et al. [6] discussed the analysis of the soil nutrient system which helps the farmer to make decisions quickly to fertilize the crops.Raspberry Pi 3 Model B unit, pH sensor, EC sensor, and soil moisture sensor are used in this model. The processing unit reads the data which is collected through the pH and EC sensors and calculates the Nitrogen, Phosphorus, and Potassium values based on the pre-defined mathematical model. Collected data are transmitted to a smartphone through Wi-Fi. In their study, Rakesh Kumar Ray et al. [7]present a novel method where soil samples are collected from different zones and each sample is divided into two parts. The one-part sample was tested through the IoT prototype, and the other part was tested through the laboratory, finally, both results were compared.This paper describes crop recommendations for 22 types of crops with distribution analysis, correlation analysis, ensembling, and performance evaluation. Limitations of this paper are: Ec sensor is used to calculate N, P, and K values. Instead of that, we can use the NPK sensor to avoid mathematical calculations. The same set of samples needs to be compared with the IoT prototype and laboratory. Data pre-processing and feature extraction. Data analysis and performing classification tasks: Training and test data split performed to perform training and testing instances. It has been done through k-fold cross-validation. Testing and validation of the model through visualization of confusion matrix Crop recommendation have been done with ensemblingtechnique using majority voting. The module was presented in detail with visualization. Limitations of this system are that location-based prediction is not done. We can implement location-based prediction with the help of a cloud-based system.

A method was proposed by the authors in [8] that allows farmers to manage and monitor their farm equipment as well as forecast their field crops using an LCD and keypad that are put in their homes. The suggested study will use the provided environmental factors to forecast which crop would be most favorable for growing. Due to this, classifier models are considered. The proposed work creates a functional prototype of an Internet of Things (IoT) device that integrates with an Android app. The device can control irrigation based on a timer, monitor farm data in real-time, predict what crops would be suitable based on weather variations and serve as a classified advertising portal. There is room for improvement in the existing crop forecast findings when additional environmental factors such as soil NPK content, UV radiation, and geographical terrain are taken into account alongside the temperature, humidity, and rainfall data already included in the model.

In their proposal for an IoT and ML-based agriculture system, ManikraoMulge et al. [9] aimed to help farmers and agriculturists utilize live metrological data from the crop field to make predictions based on the theory of metrological agriculture. This would allow for smart farming, which in turn would increase the overall yield and quality of their products. The Decision Tree Algorithm, which is employed in this system, is crucial for prediction as it makes decisions at each level of the binary tree. It is possible to graphically and unambiguously depict decision-making processes using a Decision Tree. It bases its judgments on a model similar to a tree. A popular tool in data mining for finding a way to accomplish a specific objective, it is also extensively utilized in machine learning.The study conducted by Correndo et al. [10] aimed to determine the significance of soil, weather, and cropping management factors in estimating and amplifying uncertainty in important factors impacting the nitrogen response of maize yield. Considerations in EONR include nitrogen fertilizer efficiency (NFE), yield at economic optimal nitrogen rate (YEONR), and yield without fertilizer. In order to model the N response curves, we employed Bayesian statistics, and to determine which attributes were most important for predictability, we used Extreme Gradient Boosting.

Wang et al. [11] looked at the prospect of enhancing in-season N-nutrient index (NNI) and maize grain production prediction by integrating data from 'GreenSeeker,' an optical sensor that monitors crop health and vigor using NDVI, with data from management, soil, and weather. We compared RFR to two other models: Lasso linear regression (LLR), which incorporates all plant data, and the simple regression model, which uses similar combined data from numerous sources. Researchers in northeastern China examined the effects of nitrogen fertilizer on maize yields at four different locations. A novel approach to seasonal nitrogen fertilizer recommendations has been devised by utilizing the RFR model to forecast grain production. This model can simulate the response of maize grain yield to various nitrogen fertilizer treatments at different growth phases.

Nidhi H. Kulkarni et al.[12] proposed a method named, "Enhancing Crop Productivity using an Ensembling-Based Crop Recommendation System." This proposed technique was used to accurately select crops based on soil type and other parameters, such as surface temperature and average rainfall. Random Forest, Naive Bayes, and Linear Support Vector Machinewere among the machine learning algorithms that were compatible with the suggested system. This crop recommendation system used the soil dataset input to categorize crops into two types: Kharif and Rabi. The proposed system was able to attain an accuracy rate of 99.91% when implemented. DeeptiDigheet al.in [13]) presented, "Analysis of Crop Recommendation Systems." A smart farming crop recommendation system was created by this suggested system. This research report analyzed a range of machine learning algorithms, such as SVM, C4.5, K-means, Decision Tree, Naïve Bayes, KNN, IBK, and C4.5. This study improved the system's accuracy by using the Hadoop framework for intense calculations.Aruna Varanasiet al. [14] presented an AI-powered crop guidance system for the Ramtek region aimed at increasing harvest yields. Soil types, soil features, and crop yield data gathering were the three main components of the planned system, which then used this information to recommend crops to farmers. Various machine learning methods, such as random forest, K-Nearest Neighbour, CHAID, and Naïve Bayes, were utilized by this suggested system. By implementing this suggested system, we may forecast specific crops based on specific meteorological conditions, state and district values, and other factors. As a result, our planned project would aid farmers in increasing national output by allowing them to sow the appropriate seed based on soil requirements.

The SVM was suggested by Gandhi et al. [15] to predict rice crop yields. Location, temperature, precipitation, and production are some of the variables included in the dataset utilized in this approach. Sequential minimum optimization is the classifier that has been applied to this dataset. To create the set of rules for the existing dataset, they prepared it using the Weka tool. Python results were generated using the SVM method. This paper's stated goal is to create a system that recommends crops, fertilizers, yield forecasts, and crop rotations. The user is given a crop recommendation by use of a voting-based ensemble classifier that incorporates the CHAID Classifier (Chi-square Automatic Interaction Detection), the Random Forest Classifier, and the Naïve Bayes Classifier. It will also suggest fertilizers that are appropriate for the user's crop type. The user will be given the quantity of produce if they input the area of the land. By offering different crops that can be cultivated according to the crop season and what is recommended, crop rotation becomes a reality. By adhering to the Voting-based ensemble classifier, we were able to attain a crop recommendation accuracy of 92%.

The study by Shindeet. Al in [16] offers advice to farmers on what crops to grow, how to rotate their crops, and which fertilizers to use.Farmers can access the system through their smartphones or computers. One disadvantage is that it doesn't make use of micro-level parameters.All the above methods discussed fail to address the effective crop recommendations to the farmers considering soil parameters.

A novel machine learning and IoT-based crop recommendation system, "Enhanced Crop Recommendation System (ECRS)," is introduced in this research. Based on a set of established parameters, the suggested method tries to determine which crop is suitable for the best yield. Several factors were considered, such as soil type, temperature, and humidity, to ascertain crop, with the use of recommendation algorithms based on machine learning. The proposed method accepts crop and nutrient data as inputs and returns crop recommendations as outputs.

Iii. Proposed Method

Today, farmers need an efficient crop recommendation system to boost production. The suggested system "The Enhanced Crop Recommendation System (ECRS) leverages datasets to recommend fertilizercrops. The proposed method ECRS employs several machine learning algorithms like SVM Classifier, Decision Tree, Logistic Regression, Random Forest, KNN Means, and Gradient Boost Algorithms to prescribe crops based on soil properties utilizing datasets.

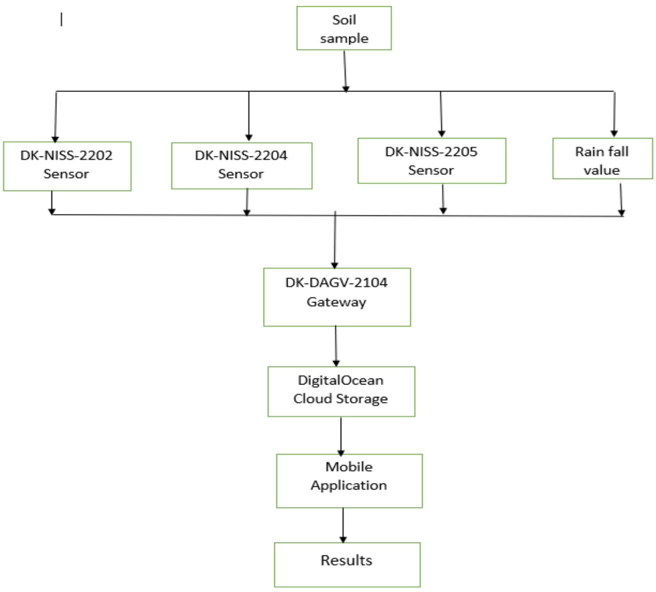

Figure 1. Framework of the proposed "Enhanced Crop Recommendation System (ECRS)

IoTIoT-based smart agriculture concept of the proposed method ECRS is described in Figure 1. The essential sensors are integrated into a Gateway. Soil properties sensor, pH sensor, and NPK sensor were all used for the IoT system. The Gateway delivers the data to the cloud which was collected through the sensors.

The suggested method ECRS works in two stages

1. Dataset

2. Applying Machine Learning M

In the first phase, the proposed ECRS uses a dataset that comprises features like Nitrogen N, Potassium P, Phosphorous K, Soil pH, temperature, andhumidity,Later in the second stage multiple machine learning models are applied to recommend the crop suitable for the nature of the soil.

The steps in the proposed approach are below.

1) Dataset Gathering
2) Noise removal pre-processing

3) Extracting Features
4) Applied ML Algorithm
5) Recommendation System

1. Dataset predicts the best crop for a given environment. This dataset covers N, P, K, temperature, humidity, and soil pH values

2. Post-collection datasets are pre-processed to allow machine learning model training. Then, encoding, outliers, and missing or partial data are examined.

3. Datasets train models. Machine learning model performance was measured byprecision, accuracy, F1 score, and recall.
4.The most accurate machine learning model recommends specific crops.

3.1 Dataset Gathering

In the dataset, different factors are considered like Phosphorus, Nitrogen, and Potassium, humidity, temperature, pH, and rainfall values. The data set is taken from Kaggle. A totalof 22 types of crops are considered to be recommendedcrops. Combining existing Indian records on precipitation, weather, and soilallowed us to construct this dataset. Factors used in the dataset are described in Table 1.

Table 1. Dataset Description

S.No	Attribute	Description
1	N	“nitrogen”
2	P	“phosphorus”
3	K	“potassium”
4	T	“Temperature in Celsius”
5	H	“Humidity in (%)”
6	pH	“Soil pH”
7	RF	“Rainfall in mm”

Table 2 shows the dataset description like Nitrogen, Phosphorus, Potassium, temperature, etc., which are required for the proposed model.

Table 2. Instances from the Dataset as a Sample

Crop	N	P	K	T	H	PH	RF
Rice	90	42	43	20.8	82.0	6.5	202.9
Maize	79	51	16	25.3	68.4	6.5	96.4
Chickpea	43	79	79	19.4	18.9	7.8	80.2
Kidney Beans	17	77	23	24.5	20.8	5.6	64.1
Pigeon peas	28	59	22	30.9	52.7	7.0	170.9

Table 3 shows the instances from the dataset as a sample as it gives the values of Nitrogen, Phosphorus, Potassium, Temperature, and Humidity values for different crops like Rice, Maize, Chickpea, etc.

	A	B	C	D	E	F	G	H
58	74	54	38	25.65553	83.47021	7.120273	217.3789	rice
59	91	36	45	24.44345	82.45433	5.950648	267.9762	rice
60	71	46	40	20.28019	82.12354	7.236705	191.9536	rice
61	99	55	35	21.72383	80.23899	6.501698	277.9626	rice
62	72	40	38	20.41447	82.20803	7.592491	245.1511	rice
63	83	58	45	25.75529	83.51827	5.875346	245.6627	rice
64	93	58	38	20.61521	83.77346	6.9324	279.5452	rice
65	70	36	42	21.84107	80.72886	6.94621	202.3838	rice
66	76	47	42	20.0837	83.29115	5.739175	263.6372	rice
67	99	41	36	24.45802	82.74836	6.738652	182.5616	rice
68	99	54	37	21.14347	80.33503	5.59482	198.6731	rice
69	86	59	35	25.78721	82.11124	6.946636	243.512	rice
70	69	46	41	23.64125	80.28598	5.01214	263.1103	rice
71	91	56	37	23.43192	80.56888	6.363472	269.5039	rice
72	61	52	41	24.9767	83.89181	6.880431	204.8002	rice
73	67	45	38	22.72791	82.17069	7.300411	260.8875	rice
74	79	42	37	24.87301	82.84023	6.587919	295.6094	rice
75	78	43	42	21.32376	83.0032	7.283737	192.3198	rice
76	75	54	36	26.29465	84.56919	7.023936	257.4915	rice

Crop_recommendation

Table 3. Sample dataset

3.2 Machine Learning Models

Various Machine Learning algorithms are used for crop recommendation. To get good accuracy eight algorithms are compared. Those eight algorithms are 1. Gradient Boosted Trees 2. Random Forest 3. Logistic Regression 4. Light GBM 5. XGBoost 6. K Nearest Neighbors 7. Decision Tree 8. SVM

Random Forest

The Random Forest algorithm is an easy-to-use and versatile method that produces reliable predictions. Random forest method is one ML technique that can be used to make predictions.

XGBoost

The gradient boosting technique XGBoost, on the other hand, builds a cluster of weak decision trees and then leverages their combined predictions to produce a more accurate result [17].

Logistic Regression

There are various variations on the Logistic Regression model, but at its essence, it uses a logistic function to describe a binary dependent variable. This makes it a popular statistical model. Regression analysis makes use of logistic regression, a subset of binomial regression, to predict the parameters of logistic models [17].

Light GBM

LightGBM is a gradient-boosting approach within an ensemble learning framework. It builds a strong learner by adding weak learners successively in a gradient descent fashion. Using methods such as Gradient-based One-Side Sampling (GOSS) minimizes the amount of time and memory needed for training [17].

Decision Tree

When training the dataset, a Decision Tree approach was employed. Through the use of a supervised learning algorithm, the decision tree method partitions the dataset containing the target qualities into progressively smaller parts. Three functions are performed by each node in a tree: root, decision, and terminal. Because the variance error source grows with increasing model complexity, tree pruning, and time series cross-validation can be used to decrease it. This method locates optimal recursive binary node splits by employing a greedy top-down strategy that locally minimizes variance at the terminal node. The use of greedy algorithms is common in decision tree classifiers. A supervised learning algorithm, it uses trees to store attributes and class labels [18]. A Decision Tree's principal function is to construct a training prototype capable of predicting the value or class of target variables by applying decision rules derived from training data.

K Nearest Neighbors

Using the K Nearest Neighbour (KNN) algorithm, crop recommendations are created. At the outset, the user is prompted to provide input details such as soil type, land type, soil texture, nitrogen, phosphorous, and potassium. Soil type, land type, and soil texture are the user-supplied variables that will be used to filter the dataset afterward [18].

SVM

Using the SVM classification approach, which sorts the many soil characteristics, one may forecast the optimum crop to produce. Anaconda Navigator is used to run the proposed algorithm to determine the crop that would be most suitable for the soil. The SVM approach is being tested for classification purposes [18].

3.3 Algorithm

Procedure_Algorithm (ECRS)

Begin

{

//Input1: Soil Characteristics**:**N, P, K, Soil pH, temperature,

and humidity

// Input2: Data Set

//Output: Recommended Crop

Step 1: Collect the Dataset using the soil characteristics

Step 2: Datasets preprocess

Step 3: Determine which features are required

Step 4. Assign 80% weight to the training dataset and 20%

weight to the testing dataset.

Step 5: Train the Machine learning models involved in

'ECRS' Proposed System.

Step 6: Test the ECRS System

Step 7: Use a highly accurate machine-learning model

to prescribe suitable crops.

}

End

Iv. Experiment And Results

In order to measure soil properties using sensors, 69 samples were taken from various fields in Nyavanandi village. The land survey number, owner's phone number, and name were also gathered together with the soil samples. With the consent of the landowner, soil samples were collected. Samples are taken at a depth of fifteen centimeters. Below figure 2 displays data collected and stored in the cloud via sensors.

Result from query 1/1

ph	soil_temp	soil_wc	soil_ec	n	p	k	ts
7.51	24.5	32.8	31.4	41	38	101	1667381456000 (2022-11-02T09:30:56.000Z)
7.51	24.5	32.8	31.3	41	38	101	1667381396000 (2022-11-02T09:29:56.000Z)
7.51	24.5	32.8	31.3	41	38	101	1667381335000 (2022-11-02T09:28:55.000Z)
7.5	24.5	32.8	31.2	41	38	101	1667381275000 (2022-11-02T09:27:55.000Z)
7.5	24.5	32.8	31.1	41	38	101	1667381215000 (2022-11-02T09:26:55.000Z)
7.5	24.5	32.9	31.1	41	38	101	1667381155000 (2022-11-02T09:25:55.000Z)
7.5	24.5	32.9	31	41	38	101	1667381095000 (2022-11-02T09:24:55.000Z)
7.5	24.5	33.1	30.9	41	38	101	1667381035000 (2022-11-02T09:23:55.000Z)
7.5	24.5	33.1	31	40	37	98	1667380975000 (2022-11-02T09:22:55.000Z)
7.49	24.5	32.8	30.9	40	37	98	1667380915000 (2022-11-02T09:21:55.000Z)

Figure2. Data collected through sensors

After collecting the data, all the eight machine learning algorithms specified are applied to the above dataset. LightGBMalgorithm performs well out of all ML algorithms applied in terms of accuracy, precision, and recall.The crop recommendation made by the LightGBM ML algorithm is taken into consideration. Later the recommended crop details can also visualized in a mobile app by the farmers immediately. Figures 3 and 4 show the crop recommendation images in the mobile app.

```
[45]: result

[45]: {'N': 41.0,
       'P': 38.0,
       'K': 101.0,
       'temp': 24.5,
       'humidity': 32.9,
       'pH': 7.5,
       'result': "['chickpea']"}

[34]: result

[34]: {'N': 0.0,
       'P': 0.0,
       'K': 0.0,
       'temp': 26.6,
       'humidity': 0.0,
       'pH': 7.88,
       'result': "['kidneybeans']"}
```

Figure3.Crop recommendation results

Figure4.Crop recommendation results in mobile app

4.1 Performance Evaluation

All eight machine learning algorithms are applied as part of the proposed method ECRS in the second stage. LightGBM ML algorithm evolved as a better one compared to other algorithms in terms of accuracy, F1 score, recall, and precision. A comparison of all the eight algorithms is depicted below.

1. Accuracy

The accuracy comparison of the applied machine learning algorithms is shown in the below figure 5.

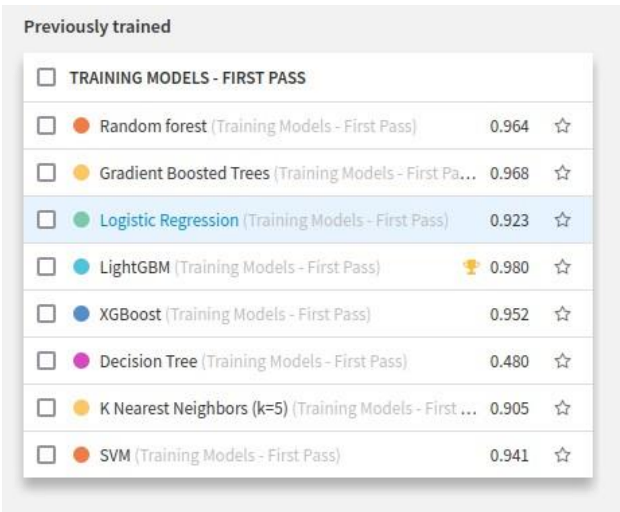

Figure 5. Accuracy comparison of the applied algorithms

The LightBGM algorithm exhibits the highest accuracy of 0.980 compared to other machine learning algorithms.

2. Precision

Precision is defined as the ratio of actual positive forecasts to total positive predictions. To rephrase, accuracy determines the proportion of positive predictions.

The precision formula is:

$$Precision = \frac{TP}{TP + FP}$$

Image by Author

The precision comparison of the applied machine learning methodsis shown in the below figure 6.

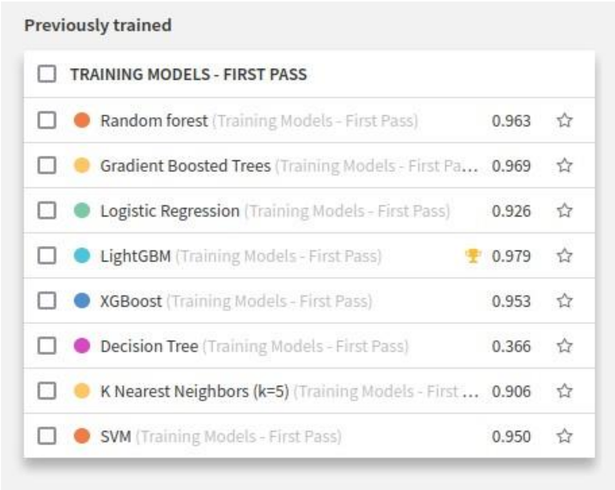

Figure6.Precision value of all the eight algorithms

The LightBGM algorithm exhibits the highest precision of 0.979 compared to other machine learning algorithms.

3. Recall

Recall is the ratio of true positives to both true positives and false negatives. Recall is a measure of how well the model can anticipate good outcomes.

The formula is as follows:

$$Recall = \frac{TP}{TP + FN}$$

Image by Author

The recall comparison of the applied machine learning methods is shown in the below figure 7.

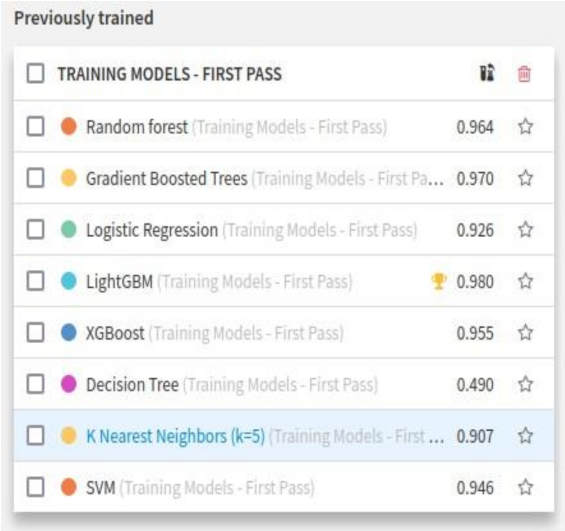

Figure 7. Recall valueforeightalgorithms

The LightBGM algorithm exhibits a recall of 0.980 compared to other machine learning algorithms.

4. F1 Score

F1scores arecalculated for eight algorithms. Thosevalues aredisplayed inbelow figure 8.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Image by Author

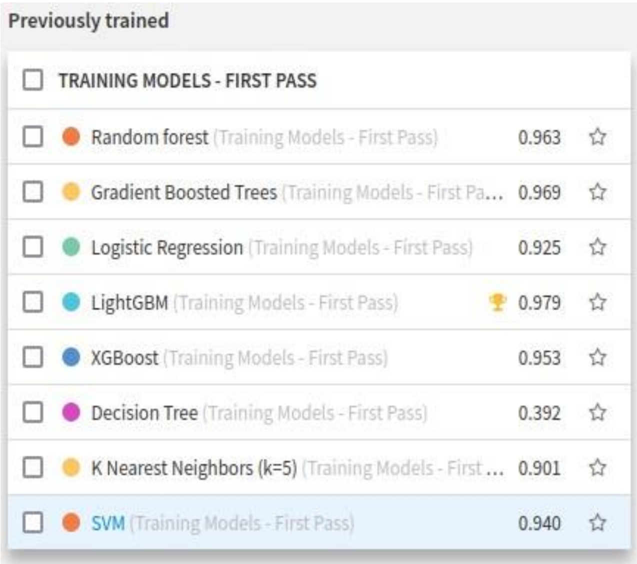

Figure8.F1 scores for theeight algorithms

The LightBGM algorithm exhibits an F1 score of 0.979 compared to other machine learning algorithms.

The results reveal that the LightBGM machine learning algorithm outperforms the other algorithms in terms of accuracy, precision, recall, and F1 score. To select the appropriate crop using the datasets and soil characteristics provided, the proposed model, 'ECRS,' uses LightBGM. Table4 shows the LightBGM Learning Model's crop recommendations.

Table 4. Recommendation of the crop – Sample output by LightBGM

Label	N	P	K	pH	Humidity	T	Crop
1	41	38	101	7.5	32.9	24.5	Chickpea
2	0	0	0	0	7.88	26.6	Kidneybeans
3	44	39	105	7.0	26.9	25.6	Soyabeans

V. Conclusion

Merging of agriculture problem statements with ML algorithms has led to various applications.Oneofthoseistheproposed croprecommendationmethod "ECRS", based oncertainparametervalues. The dataset is collected from the Kaggle to train the model. This work is focused on 22 types of crops. Eight Machine Learning algorithms are compared for the good working of the system. Eight algorithms' accuracy is calculated, among those Light GBM algorithm got high accuracy with 98%. Performance metrics precision, recall, F1 score, and Log Loss were also calculated for all eight algorithms. Among those four performance metrics,the Light GBM algorithmhasprovenbestalgorithmforthedatasettakentotrainthemodel.Byconsideringall thesefactorsLightGBMMachineLearningalgorithmisusedforcroprecommendation.Input data will be fetched from the cloud server which is collected through the sensors. Based on thevaluescroprecommendationswillbesuggestedtothefarmerintheform oftextmessagesin regional language (Telugu). This system helps to choose efficient crops for specific soil to get bettercropyield.Datastoredina cloudserverwhichiscollectedthroughthesensorswillbeused to analyze soil parameters.

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References

[1] Maduranga, M. W. P., and RuvanAbeysekera. "Machine learning applications in IoT based agriculture and smart farming: A review." *Int. J. Eng. Appl. Sci. Technol* 4.12 (2020): 24-27.

[2] Idoje, Godwin, TasosDagiuklas, and Muddesar Iqbal. "Survey for smart farming technologies: Challenges and issues." *Computers & Electrical Engineering* 92 (2021): 107104.

[3] Patil, Rekha J., Indira Mulage, and NishantPatil. "Smart agriculture using IoT and machine learning." *Journal of scientific research and technology* (2023): 47-59.

[4] Rezk, Nermeen Gamal, et al. "An efficient IoT-based smart farming system using machine learning algorithms." *Multimedia Tools and Applications* 80 (2021): 773-797.

[5] Rani, Sita, et al. "Machine learning-based optimal crop selection system in smart agriculture." *Scientific Reports* 13.1 (2023): 15997.

[6] Senevirathna, Amnn, et al. "Development of a Raspberry Pi-based soil nutrient analyzing system for crop cultivation." *2021 IEEE 10th Global Conference on Consumer Electronics (GCCE)*. IEEE, 2021.

[7] Ray, Rakesh Kumar, Saneev Kumar Das, and Sujata Chakravarty. "Smart crop recommender system-a machine learning approach." *2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*. IEEE, 2022.

[8] Sarpal, Deepika, et al. "AgriWealth: IoT based farming system." *Microprocessors and Microsystems* 89 (2022): 104447.

[9] Mulge, Manikrao, et al. "Agricultural crop recommendation system using IoT and ML." *The International journal of analytical and experimental modal analysis* 12.6 (2020).

[10] Correndo, Adrián A., et al. "Attainable yield and soil texture as drivers of maize response to nitrogen: A synthesis analysis for Argentina." *Field Crops Research* 273 (2021): 108299.

[11] Tian, Zhixi, et al. "Designing future crops: challenges and strategies for sustainable agriculture." *The Plant Journal* 105.5 (2021): 1165-1178.

[12] Kulkarni, Nidhi H., et al. "Improving crop productivity through a crop recommendation system using ensembling technique." *2018 3rd international conference on computational systems and information technology for sustainable solutions (CSITSS)*. IEEE, 2018.

[13] Dighe, Deepti, et al. "Survey of crop recommendation systems." *IRJET* 5 (2018): 476-481.

[14] Akkem, Yaganteeswarudu, Saroj Kumar Biswas, and Aruna Varanasi. "Smart farming using artificial intelligence: A review." *Engineering Applications of Artificial Intelligence* 120 (2023): 105899.

[15] Gandhi, RR Rubia, et al. "Machine learning approaches for smart agriculture." *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*. IEEE, 2022.

[16] Shinde, Mohini, et al. "Plant Growth Recommendation System based on Weather Conditions and Soil Patterns using Machine Learning and Deep Learning Techniques." *2022 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)*. IEEE, 2022.

[17] Shaikh, TawseefAyoub, et al. "Machine learning for smart agriculture and precision farming: towards making the fields talk." *Archives of Computational Methods in Engineering* 29.7 (2022): 4557-4597.

[18] Kwaghtyo, Dekera Kenneth, and Christopher Ifeanyi Eke. "Smart farming prediction models for precision agriculture: a comprehensive survey." *Artificial Intelligence Review* 56.6 (2023): 5729-5772.