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AN EXPERIMENTAL ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR CROP RECOMMENDATION

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Abstract

Taking a country into consideration where agriculture remains the primary occupation and farming still happens using conventional methods, the farmers are not able to produce anticipated yields. Modern farming strategies called precision farming play a vital role in improving crop yield and generating more profit for the farmers. This includes recommendations of crops that are suitable for specific fields based on soil conditions, temperature, rainfall, and humidity. To solve this problem, crop recommendation systems play an important role. In this research work, a crop recommendation system (CRS) was implemented using various machine learning algorithms that include random forest, decision trees, extreme gradient boosting (XG boost), and K-nearest neighbors (KNN). Experimental analysis was performed on the dataset collected from Kaggle. The Random Forest algorithm outperforms XG Boost, Decision Tree, and KNN with high accuracy and F1 score of 99.3% and 99.01% respectively. Hyperparameter tuning is additionally performed on XG Boost and Random Forest algorithms to improve accuracy. After hyperparameter tuning, the Random Forest algorithm outperforms XG Boost with an accuracy of 99.5%.

1.0 INTRODUCTION

In the present era, a significant increase in the use of technology helps individuals to overcome the challenges in various domains such as agriculture, e-commerce, stock market, etc. In the agricultural domain, failure in choosing the suitable crop for cultivation, based on the field conditions may lead to a reduction in yield and financial losses for farmers [15]. The farmers need to choose suitable crops to improve the crop yield [11]. The main factors to be considered for growing suitable crops in the specific field are soil properties such as nitrogen (N), phosphorus (P), potassium (K), and pH, as well as weather conditions such as temperature, rainfall, and humidity [16].

The three most critical elements for growing crops are N, P, and K. N helps in producing rich stems and leaves that appear dark green in Lettuce, Broccoli, Cabbage, and Herbs. P aids in the initial growth of plants including flowering and production of seeds. P helps in growing crops like tomatoes, peppers, squash, cucumbers, and peppers after flowering. K is essential in enhancing the flavor of plants, increasing their resistance to diseases and pests, and improving stress

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tolerance and health of plant roots for growing Garlic, Onion, Turnip, Carrot, and Radish crops. The measurement of soil pH is a scale for the level of soil acidity or alkalinity value measured from 0 to 14. pH value of 7 denotes a neutral position. This changes the chemical forms of some nutrients, and their reaction processes involved in taking up into plants.

Most plants grow at a pH that ranges from 5.5 to 7.5. Many plants, however, have evolved to flourish at pH levels outside of this range. Various plant species have various weather requirements, such as optimal temperature, rainfall, and humidity ranges for planting and growth.The main goal of CRS is to assist farmers in decision-making for selecting appropriate crops for a specific field environment [17,18]. This will aid in increasing productivity and, as a result, increase profitability. A crop recommendation application was developed using ML algorithms in which the user should enter soil nutrient values of N, P, K, and Ph and the climatic condition values of temperature, rainfall, and humidity. The application will forecast the suitable crop the farmer should produce as per the specified field and climatic conditions.

In recent years, the agricultural industry has incorporated machine learning (ML) approaches [19,20] aimed at providing farmers with specialized and precise advice based on their specific needs. These ML systems excel in detecting insignificant data patterns and correlations that would be difficult, if not impossible, to detect manually [7]. As a result, they enable the creation of exact estimates about crop compatibility, possible yields, and the most effective farming methods.

This paper is structured as follows. The literature review is discussed in Section 2, Section 3 explains Methodology, Section 4 shows Experimental Results, and Section 5 describes Conclusion and Future Scope.

2.0 LITERATURE REVIEW

The various methods discussed in the literature can be categorized into two categories: i. Techniques based on Machine Learning (ML), and ii. Approaches based on Deep Learning (DL).

2.1 Crop Recommendation using Machine Learning (ML) Techniques

A review on the various ML techniques used in agriculture domain for crop recommendation is presented as follows; Atharva Jadhav et al. [1] build various models using decision trees, logistic regression, random forests, and XG boost. The authors calculated the accuracy of those models to evaluate the effectiveness of various classification techniques. Random Forest outperforms other algorithms with an accuracy of 98.9%.

Mohamed Bouni et al. [2] used Random Tree, KNN, Nave Bayes, and Neural Network Deep Reinforcement Learning (DRL) approaches to develop Efficient Recommender Systems in Smart Agriculture. By combining deep learning and reinforcement learning, DRL can deal with uneven data and performs better than the other algorithms with an accuracy of 98.6%. Dhruvi Gosai et al. [3] conducted a study on crop recommendation using ML techniques. The authors conducted experimental analysis on the crop recommendation using Decision Trees, SVM, Naive Bayes, Random Forest, Logistic Regression, and XGBoost algorithms. XGBoost performs better than the other algorithms.

Shafiulla Shariff et al. [4] used ML approaches for crop recommendation. The authors developed a model using ML algorithms, that recommends best harvest based on soil characteristics. The authors conducted experimental analysis on models implemented using Gradient Boosting, Decision Trees, Random Forest, Naive Bayes, and KNN approaches. The gradient boosting algorithm achieved the highest accuracy among the other algorithms. Nidhi H Kulkarni et al. [5], implemented crop recommendations using the dataset consisting of 4 crops: wheat, cotton, rice, and sugar cane. Implemented models using naive Bayes, random forest, and Linear SVM techniques. Combining these three algorithms proposed Majority Voting Technique to achieve higher accuracy and for accurate prediction of crops to be cultivated.

Maaz Patel et al. [6], developed an intelligent system that can suggest suitable crops to farmers, by considering Nitrogen, Potassium, Phosphorus, PH Value, Rainfall, Humidity, and Temperature factors. Developed models using Gaussian NB, SVM, and Decision Tree and achieved the best accuracy with the Gaussian NB Technique.

2.2 Crop Recommendation using Deep Learning (DL) Techniques

A review of various DL techniques [10] used in the agriculture domain for crop recommendation is presented as follows; Tanmay et al. [13] designed a crop recommendation system using neural networks. The system uses sensors to measure soil moisture levels, humidity, and temperature in the field. Data from these sensors is gathered via an ESP8266 Wi-Fi Module, and a Raspberry Pi 3 serves as the local

network for displaying the results. Literature review findings of crop recommendation using machine learning and deep learning techniques are summarized in Table 1.

Table 1: Review of machine learning and deep learning techniques for crop recommendation

Authors, Reference	Objective	Methodologies	Results	Pros and Cons
Atharva Jadhav et al. [1]	To provide advice on crops to farmers using machine learning techniques.	Random Forest, Decision Tree, Logistic Regression, XG Boost	Random Forest performed better with 98.9% accuracy.	Developed a model for recommending crops based on soil and regional characteristics of the field, but weather factors are not taken into consideration.
Mohamed Bouni et al. [2]	To provide guidance on crops to farmers for precision agriculture using the DRL approach.	DRL, Naïve Bayes, KNN, Decision Tree, Random Forest	The DRL and Random Forest classifiers attained similar accuracy.	With a larger dataset, DRL could achieve precise results.
Dhruvi Gosai et al. [3]	To provide guidance on crop selection to farmers by analyzing sensor data using machine learning techniques.	Decision Trees, SVM, Naive Bayes, Random Forest, Logistic Regression, and XGBoost	XGBoost performed better with 99.3% accuracy.	Lack of user interface development.
Shafiulla Shariff et al. [4]	To develop a recommendation system using machine learning algorithms that recommends crops suitable for a specific soil type.	Gradient Boosting, Decision Trees, Random Forest, Naive Bayes, and KNN	Gradient Boosting performed better with 98.18% accuracy.	Accuracy was a bit low compared to other previous works.
Nidhi H Kulkarni et al. [5]	To develop a crop recommendation system using ensembling machine learning techniques.	Majority Voting Technique is combined with naïve Bayes, random forest, and Linear SVM techniques.	The average classification accuracy of 99.91% is obtained when independent base learners are combined.	Crops are classified into kharif and Rabi crops. However, crops to be grown in specific field are not recommended.
Maaz Patel et al. [6]	To develop a crop recommendationsyste m using machine learning techniques.	Gaussian NB, SVM, and Decision Tree.	Decision Tree and Gaussian NB attained similar accuracy of 99.3%.	Lack of user interface development.
Tanmay et al. [13]	To develop a crop recommendation system to predict the suitable crop using Neural networks.	Neural Networks	The model predicts the most suitable crop using the ANN algorithm.	Developed a model to predict suitable crops based on field soil moisture, temperature, and humidity information collected from various Sensors. This work can be extended to automate the irrigation system in the field.
Kanga Subba Raja et al. [14]	To develop a recommendation system for recommending crops to farmers by analyzing satellite images of the field.	Soil supplements are investigated using hybrid approach by combining Neural Network and Image Processing. Deep Recurrent Q-Network (DRQN), Deep Q-learning algorithm, CNN, RNN and HNN.	HNN performed better with 99% accuracy.	Developed a model to recommend crops based on field soil supplements, temperature, humidity, and water features information collected from satellite images. By utilizing water body extraction approaches, this work can be extended to extract water features.

3.0 METHODOLOGY

An Overview of the CRS is shown in Figure 1.

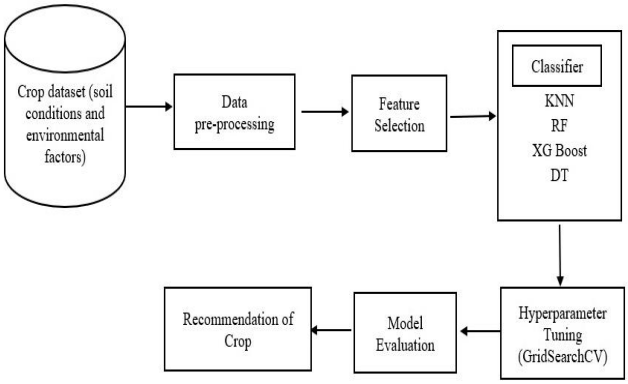

Figure 1: Overview of CRS

3.1 Dataset Collection

The Crop Dataset is collected from Kaggle repository [15]and consists of 2200 rows and 8 columns. The dataset consists of parameters such as N, K, P, temperature, humidity, pH, rainfall, and crop labels. This dataset includes 22 different crops including rice, chickpeas, pigeon peas, corn, mung beans, black beans, moss beans, lentils, pomegranates, bananas, mangoes, kidney beans, grapes, watermelons, oranges, cantaloupe, apples, and papaya. The sample dataset is shown in Figure 2.

3.2 Data Preprocessing

Data obtained from various sources may not be accurate and it might be imbalanced. So, data preprocessing is the key step for further analysis. The primary objective of this is to filter out the redundant values and finding the missing values. Mean Imputation is used for handling Missing and null values in the dataset to maintain the quality and completeness. Categorical data is converted to numerical data using Label Encoder.

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
...	...	...	...	...	...	...	...	...
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

2200 rows × 8 columns

Figure 2: Sample dataset for CRS

3.3 Feature Selection

It's important to identify which features (input variables) are most relevant for crop recommendation. Domain knowledge and data analysis techniques can help in selecting the most informative features. In this work correlations between features are plotted using a heatmap.

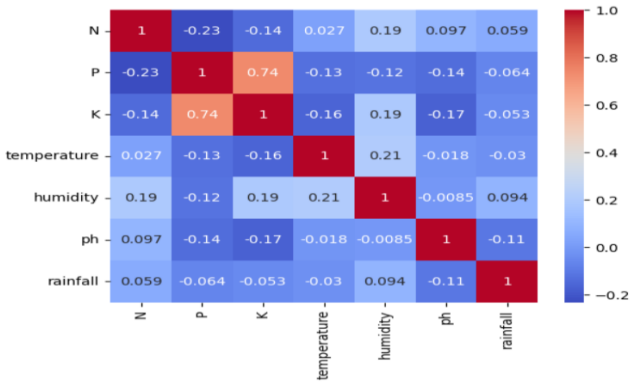

Figure 3: Correlation matrix between the features

The color intensity in the heatmap from Figure 3 shows the strength of the correlation between various environmental factors affecting crop yields. We have assumed a correlation coefficient of 0.8 and hence all the features are necessary to us.

3.4 Train-Test Split Strategy

The primary objective of dividing datasets into testing and training sets is to assess the model's performance and capacity to provide precise predictions on new, unknown data. A training dataset typically consists of 80% of the total data and is the primary resource for instructing and guiding the machine learning model. The model learns about the dataset's intrinsic patterns, correlations, and trends. The remaining 20% is the test dataset, used to evaluate the model's performance. It is segregated from the training set to ensure that the model meets it for the first-time during testing.

3.5 Model Assessment

The experiments were carried out using KNN, Decision Tree, XG Boost, and Random Forest algorithms. The implementation details are presented as follows.

3.5.1 Decision tree

Although decision tree algorithms are mostly used in classification problems, they can also be applied to regression problems. It is a tree-like structure consisting of a root node, a leaf node, and an intermediate node. At the outset, the algorithm begins at the root node, representing the entire dataset. During the tree's construction, it employs an attribute selection measure to identify the most suitable attribute within the dataset. This pivotal attribute serves as the basis for partitioning the tree into subtrees, with each subtree associated with a specific attribute value or range. This partitioning process continues iteratively until the algorithm reaches a leaf node. The attribute selection measure used is entropy and information gain. The formula used for calculating them is as follows:

$$\sum_{i=0}^{n} p(i) * \log_2 p(i) \quad (1)$$

Where, p(i) is the probability of selecting an example from class i. The information gain of the current node S because of the selected feature X is:

$$IG\ (S,X)\ =\ E(S)\ -\ E\ (S,X) \quad (2)$$

The best IG of all characteristics is chosen as the decision tree's root node, generating a subtree. There is no additional segmentation or splitting after reaching a leaf node. Instead, the leaf node incorporates the ultimate judgment or prediction for the given instance, making it the decision tree's terminal point. As a result, a decision tree's structure represents a hierarchical representation of decision rules, with each route from the root node to the leaf nodes defining a distinct decision process based on characteristics and values.

3.5.2 Random forest

Random forests are an ensemble ML algorithm used for both classification and regression. Ensemble methods improve the performance of ML algorithms

by combining multiple learners. This classifier comprises multiple decision trees, each trained on distinct subsets of a provided dataset. The accuracy and efficiency are improved, and asthe random forest is a combination of decision trees, it overcomes overfitting of data issues, and normalization of the dataset is also not necessary.

The working process of random forest is explained in the following steps:

1. Selecting various random samples with replacement-Here the data selected from the dataset may be repeated more than in one or more trees so the output of the data will be more accurate.
2. Decision Trees to be drawn for the sample tree are trained on a sample of observations (known as a bootstrap sample) and this is known as a bag. The sample that is not used for trainingis called an out-of-bag (OOB) sample.
3. Choosing N number of trees- After training, the OOB sample is tested on each trained model,then an output is obtained for that bootstrap sample.
4. Repeat both 1 and 2 steps-This should be done to get an accurate output as random data should be taken many times to avoid errors.
5. Assign the class labels for the data by doing bootstrap aggregation and checking the majority number of votes and get the output class label.

3.5.3 K-nearest neighbours

The KNN algorithm is primarily used for classification tasks. It compares a new data point to the values in each dataset, with each data point belonging to a separate class or category. Choose a value for K, which specifies the number of neighbouring neighbours to consider. It measures how far apart the new data point is from every other data point in the dataset. The list of dataset data points is then sorted according to how close they are to the new data point by ascending these distances. Then, using the estimated distances, find the most nearby neighbours to the new data point. These are the data points that are most like or near the new entry. KNN operates under the assumption that data points sharing similar attributes are likely to fall within the same category, and it assigns categories to data points by considering the majority consensus of their nearest neighbours.

3.5.4 Extreme gradient boost

XG Boost is one of the boosting algorithms, and it stands for Extreme Gradient. Generally, Boosting refers to combining weaker models with stronger models to increase accuracy. In XG Boost, the trees are built one after the other, with each one aiming to reduce the errors committed by the one before it. The following are the steps for implementing XG Boost:

1. In the initial stage, the total dataset is given to the models.
2. To calculate the errors based on the previous models to predict accurate class labels.
3. The next step is to build a predictive model to build those errors and they are corrected usinglearning rate.
4. The last step is to add the model to the ensemble of the models and this process is continueduntil all the class labels are correct.

3.6 Tuning of Hyperparameters

Tuning hyperparameters is an important step in tuning ML models to improve performance. Hyperparameters are configuration settings that are set before training the model, rather than being learned from data. Tuning is finding the best combination of hyperparameters to improve a model's predictive accuracy, generalization, and efficiency.

3.6.1 Random forest hyperparameters tuning

Random forest model is optimized by fine-tuning parameters like min samples leaf, max depth, max features, and min samples split through the GridSearchCV method. This involved exploring a range of potential values for these parameters and selecting the best-performing values from the options. As a result, the default parameter settings were adjusted by setting the maximum depth of tree value to 20, the maximum number of features to "sqrt," the minimum sample leaf value to 2, the minimum sample split value to 5, and the number of estimators to 50.

3.6.2 XGBoost hyperparameters tuning

The GridSearchCV method is used for optimizing the XG Boost model by adjusting the minimum sum of weights of observations required in a child, the number of estimators, the learning rate, and the maximum depth of tree parameters. This process includes examining a wide range of possible values for these parameters and selecting the most appropriate values from the available choices. As a result, the default parameter settings were adjusted by setting the learning rate to 0.2, maximum depth of tree to 1, minimum sum of weights of observations required in a child to 1, number of estimators to 200.

3.7 Recommending the Crop

CRS can recommend suitable crop/crops, once the model has been trained and validated. The model will predict the suitable crops for the specified field

according to the given input characteristics such as soil conditions, meteorological data.

4.0 EXPERIMENTAL ANALYSIS

The experimental analysis was performed using a system equipped with an 8th generation Core i5 processor, 8GB of RAM, and a 500GB SSD hard disk. The analysis involved applying the XG Boost, Decision Tree, KNN, and Random Forest algorithms in Python to evaluate trained models using the crop dataset sourced from Kaggle.

4.1 Validation

The model performance is assessed using the metrics accuracy and F1-score. The Table 2 shown below represents the F1 scores achieved by the trained models using KNN, Decision Tree, Random Forest, and XG Boost algorithms.

Table 2: F1 score of various trained models in percentage.

S/N	Model	F1 Score
1	Decision Tree	96.2
2	KNN	95.1
3	Random Forest	99.01
4	XG Boost	98.6

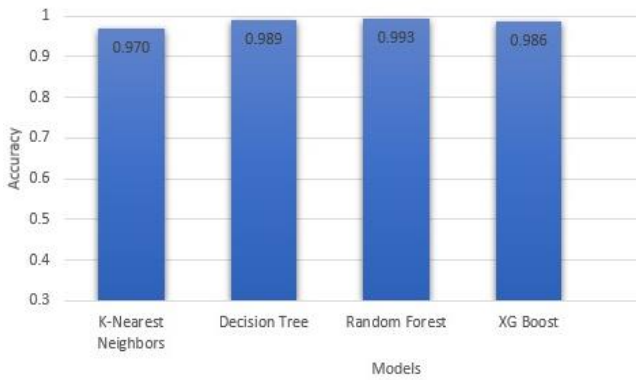

Figure 4: Experimental analysis of machine learning algorithms before hyperparameter tuning.

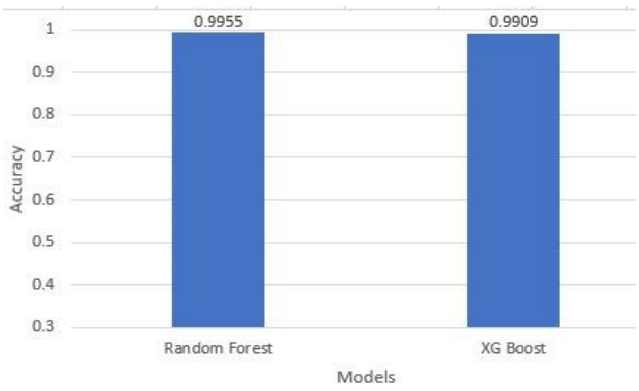

Figure 5: Experimental analysis of machine learning algorithms after hyperparameter tuning.

Figure 4 shows the accuracies of trained models using KNN, Decision Tree, Random Forest, and XG Boost algorithms. Figure 5 shows the accuracies of trained models using Random Forest and XG Boost algorithms after tuning hyperparameters. From the above results, it is observed that the Random Forest algorithm achieved a higher accuracy and F1 score of 99.3% and 99.01% respectively compared to XG Boost, Decision Tree, and KNN without hyperparameter tuning. After hyperparameter tuning also Random Forest got the highest accuracy of 99.5% compared to XG Boost algorithm.

4.2 User Interface

In this work CRS is implemented using the model build with Random Forest algorithm. CRS is developed using Python in the Flask integrated development environment (IDE) to develop the graphical user interface (GUI). Figure 6 shows the input and output Screenshots of CRS.

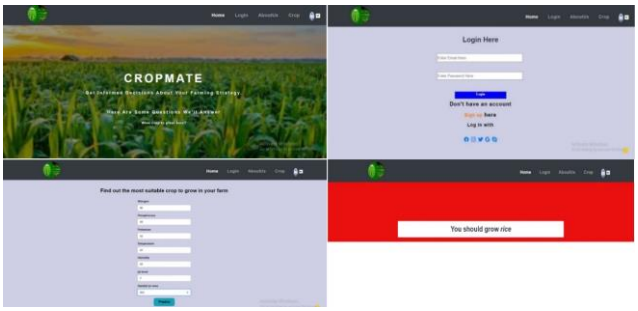

Figure 6: Input and output screenshots of CRS

5.0 CONCLUSION AND FUTURE SCOPE

The CRS powered by ML offers valuable insights to farmers for better decision-making. By analyzing various factors like soil, climate, and historical data, the system suggests suitable crops. From the experimental analysis carried out in this research work, it is observed that the Random Forest algorithm outperforms XG Boost, Decision Tree, and KNN with an accuracy and F1 score of 99.3% and 99.01% respectively. To improve accuracy, hyperparameters are tuned additionally for Random Forest and XG Boost algorithms. After employing hyperparameter tuning, the Random Forest algorithm outperforms XG Boost with an accuracy of 99.5%. The CRS implemented in this research work simplifies plant selection and makes it easier for farmers to choose the right crops for their land.

The future scope of this research work is improving model performance using Deep Learning algorithms. Integrating real-time data from various sources, including weather forecasts and IoT devices, can

provide timely and precise recommendations, adapting to dynamic environmental conditions.

REFERENCES

[1] Atharva, J., Nihar, R., Pranay, J., and Yash, G. "Crop Recommendation System Using Machine Learning Algorithms", *International Journal of Engineering Research and Technology (IJRET)*, vol. 9 Issue 04, pp. 1227-1230, 2022.

[2] Mohamed, B., Badr, H., Khadija, D., and Samira, D. "Towards an Efficient Recommender Systems in Smart Agriculture: A deep reinforcement learning approach", *ELSEVIER*, vol. 203, pp. 825-830, 2022.

[3] Dhruvi, G., Chintal, R., Rikin, N., Hardik, J., and Axat, P. "Crop Recommendation System using Machine Learning", *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol.7 Issue 07, pp. 554-557, 2021.

[4] Shafiulla, S., Shwetha, R. B., Ramya, O. G., Pushpa, H., and Pooja, K. R. "Crop Recommendation using Machine Learning Techniques", *International Journal of Engineering Research and Technology (IJRET)*, vol.10, Issue 11, pp. 199-201, 2022.

[5] Nidhi, H. K., Srinivasan, G. N., Sagar, B. M., and Cauvery, N. K. "Improving Crop Productivity Through a Crop Recommendation System Using Ensembling Technique", *International Conference on Computational Systems and Information Technology for Sustainable Solutions (CSITSS)*, pp. 114-119, 2018.

[6] Maaz, P., Anagha, R., and Vansh, P. "Crop Recommendation System using Machine Learning", *International Scientific Journal of Engineering and Management*, 2021.

[7] Nischitha, K., Dhanush, V., Mahendra, N. A., and Manjuraju, M. R. "Crop Prediction using Machine Learning Approaches", *International Journal of Engineering Research and Technology*, vol.9 Issue 08, August-2020 ISSN: 2278-0181.

[8] Kumar, Y., Jeevan, N., Spandana, V., Vaishnavi, V. S., Neha, K., and Devi, V. G. R. R. "Supervised Machine Learning Approach for Crop Yield Prediction in Agriculture Sector", In *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, pp. 736-741. IEEE, 2020.

[9] Yash, S., Harsh, G., Hamish, D., Divya, K., Amogh, A. D. K., and Umang, G. "Comparison of Self Organizing Maps and Sammon's Mapping on agricultural datasets for precision agriculture", *International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*, 2015.

[10] Kamatchi, S. B., and Parvathi, R. "Improvement of Crop Production Using Recommender System by Weather Forecasts", *Procedia Computer Science* 165 (2019): 724-732.

[11] Bhuvan, S., Alankriti Jain, and Sanjeetha, J. "DigiFarm– A Machine Learning based holistic Crop Prediction Platform for Farmers", *NVEO-NATURAL VOLATILES & ESSENTIAL OILS Journal| NVEO* (2021): 11112- 11129.

[12] Tanmay, B., Aqsa, M., Mayuresh, B., Soham, D. "Crop Recommendation System Using Neural Networks", *International Research Journal of Engineering and Technology*, vol. 5(IRJET), Issue 05, pp. 1475-1480, 2018.

[13] Kanaga, S. R. S., Durai, A. S. S. L., Praveenkumar, R., and Balaji, V. "An Intelligent Crop Recommendation System using Deep Learning", *International Journal of Intelligence Systems and Applications in Engineering (IJISAE)*, pp. 423-428, 2019.

[14] Dataset is taken from Kaggle repository [https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset]

[15] Jain, A. "Analysis of growth and instability in the area, production, yield, and price of rice in India", *Journal of Social Change and Development* pp. 46-66, 2018.

[16] Saranya, N., and Mythili, A. "Classification of soil and crop suggestion using machine learning techniques", *Int J Eng Res Technol* 9(02), pp. 671–673, 2020.

[17] Pudumalar, S., and Ramanujam, E. "Crop Recommendation System for Precision Agriculture", *IEEE Eighth International Conference on Advanced Computing (ICoAC)*, 2020.

[18] Anitha, A., and Acharjya, D. P. "Crop suitability prediction in Vellore District using rough set on fuzzy approximation space and neural network", *Neural Computing and Applications*, Vol.30, No.12, pp. 3633-3650, 2018.

[19] Garanayak, M., Goutam, S., Sachi, N. M., and Alok, K. J. "Agricultural Recommendation System for Crops Using Different Machine Learning Regression Methods", *International Journal of Agricultural and Environmental Information Systems (IJAEIS)*, Vol. 12, No. 1, pp. 1-20, 2021.

[20] Doshi, Z., Nadkarni, S., Agrawal, R., and Shah, N. "AgroConsultant: Intelligent Crop Recommendation System Using Machine Learning Algorithms", *Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)*, pp. 1-6, 2018.