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A Comprehensive Overview of Machine Learning based Crop Recommendation Analysis

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Abstract: — Today in the world, the crop recommendations and predictions are highly required by the farmers to enhance the production of the crop. The paper will set out to review the different studies conducted on crop recommendations to enhance the crop production in India. The thorough research of multiple literature works can provide an insight into the fact that machine learning (ML) techniques play a crucial role in crop forecasting and advisory. The different ML algorithms that have been very effective in predicting the results are addressed with both pros and cons. This paper discusses the parameters employed in datasets, as well as, standard procedure employed to forecast the crop recommendations. Lastly different ML and crop prediction performance indicators are given. This whole paper provides the discussion of crop recommendation methodology.

Keywords: Crop Recommendations, crop prediction, Machine Learning, AI, DL. .

1. Introduction

Modern agriculture is progressively relying on advanced crop suggestion frameworks (CRS) enabling the agriculturalists to optimize their processes in regard to various factors, among them being climate variability, soil characteristics and water availability. Introduction of co-operating contexts like Streamlit into these systems is a significant advancement over traditional farming methods and helps make web applications that can visualize and interact with complex farmed information, fast and easy to create and deploy [1, 2]. Despite these developments, the effectiveness of CRS is limited, at times, by the intricate and challenging dimensional features of cultivated data, and thus it is challenging to manage and interpret data. These drawbacks of CRS hinder them in their ability to process complex data that occurs in vibrant interactions in cultivated habitats. Traditional ML techniques often cannot successfully address this complexity to provide accurate or flexible suggestions to a changing situation [3, 4]. The new field of advanced ensemble learning has begun to demonstrate its capability of dealing with these concerns by providing more accurate and dependable result support [5, 6]. Nevertheless, despite all their proven efficiency in a variety of disciplines, the total possibility of using such technologies along with Streamlit to enhance the level of user engagement remains largely untapped and unexplored in precision agriculture.

Crop recommendation (CR) is crucial in the contemporary agricultural field, and using ML algorithms has become a potentially feasible method to enhance agricultural output and optimize crop selection. Several studies have studied the aim of the ML algorithms to suggested the right crop to be cultivated by farmers where there are several factors like past records, soil type, and weather conditions. The aim of these the aim of research is to provide the knowledge necessary to manufacturers so that they obtain notified results that will increase crop delivery, minimize losses, and enhance the quality of crops in general.

In academic sources, a range of innovative solutions is recommended to solve the dilemma that relates to CR with the help of ML algorithms. It described a hybrid technique known as Wrapper- Part-Grid that used a partial C4.5 decision tree classifier together with wrapper feature selection and hyperparameter optimisation. The approach depicted improvements in precision and performance in crop recommending, thus highlighting the improvements in the field of crop advice. However, unanswered questions are on the relevancy of these strategies in different farming environments and their scalability.

In addition, scholarly studies have emphasized the need to incorporate a number of factors, viz., soil structure, weather changes, and socioeconomic status, in models that propose crops choices. During the inception of CR models by employing different processes of ML, studies have emphasized the importance of feature relevance scores in determining characteristics that affect the model performance. The issue of data quality, model generalisation and real world performance evaluation should also be tackled to verify the reliability and applicability of the models in various agricultural situations. This paper seeks to examine the different CR insights with the help of ML. The paper describes the various algorithms to improve the superior insights regarding the soil situation and ecological factors to improve the crop recommendation.

The rest of the paper is continued in the following manner where section 2 presents the literature review on the latest trend in crop recommendations and section 3 justifies the method of crop recommendations based on ML algorithms. Section 4 provides the sample datasets which can be used to make better crop recommendation. In section 5, the performance measures typically applied in prediction of ML and crop usually state them. In section 6, the conclusions will be provided.

2. Related Work

Musanase et al. [7] outlines an entire process of making recommendations of crops and fertilisers which are supposed to enhance agriculture in Rwanda. The system consists of two prediction models, in which machine learning model is used to predict the crops and rules model is used to predict the fertiliser. The crop suggestion system is a neural network model which was trained on the list of known Rwandan crops and the nutrients, phosphorus, potassium, and pH level required to grow the crops. The system proposing fertiliser takes a rule-based method to provide individualised ideas upon the basis of the already assembled tables.

The paper by Navod et al. [8] offered an overview of the AI-driven precision agriculture and associated research, and later on propose an innovative cloud based machine learning platform to provide crop recommendation to assist agriculturalists to decide on which crops to be harvested according to numerous established variables.

Apat et al. [9] analyzed the development of AI system to achieve better precision agriculture through high quality and accuracy of crop yields. The Industry 4.0 feature selection the study provides the recommendation system that uses AI and a group of ML systems as its solution. The data used in this project was acquired in Kaggle and properly labeled. To monitor the nutrition of the soil and provide specific recommendations to crops, Islam et al. [10] propose a new Internet of Things (IoT) device that operates with the help of ML. This device real-time captures the levels of soil nutrients, moisture, humidity, temperature, and FC-28, DHT11, and JXBS-3001 sensors. One uses the MQTT protocol to transmit the obtained data to a server. Based on machine learning algorithms, the collected data is refined to generate customised recommendations, including a list of crops that have the potential to yield high harvest, the names of fertilisers and the quantities to be used, considering the needs of crops and the nutrients in the soil.

In CR purposes, Senapaty et al. [11] published an IoTSNA-CR model, which regulates the use of the IoT to categorize the soil nutrients. To ensure that the soil passes through its optimum, the model proposes to minimise the applied fertiliser. The first is that cultivation lands are monitored with the help of IoT sensors. Next, this information is stored in the cloud with the help of memory services. This data is available in the cloud to an Android app. Subsequently, the results are pre-tested and analysed after some time through the application of different learning methods.

The proposed model by Lavanya et al. [12] refers to the information of NPK sensors to give specific recommendations that can be used by farmers to optimally manage fertilisers. Using sensor data, ML procedures as well as agronomic expertise the approach considers the distinct needs of different crops and soil types and provides suitable and personalised nutrition recommendations. Nitrogen concentration in soil is one of the measurements the system takes through NPK sensors that are installed in the field. Machine learning algorithms analyze this data in order to ascertain whether there is a relationship between the level of nutrients and the yield of crops.

Based on machine learning, Dipto et al. [13] created and presented a CRS that considers NPK. values when proposing the most appropriate crop that should be planted in a particular type of soil based on a range of significant parameters. This model will be an important aspect in our agricultural sectors to ensure that we achieve maximum competence and extract maximum out of our fertile land to match the demands of our nation.

The creation of a self-sufficient CRS capable of assessing the health of soil and a database of well-chosen generic types of crops was also part of Celeste et al. [14]. It relied on a system of sensors to determine the soil fertility,

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moisture, temperature, and pH. The construction of a fuzzy logic model to predict crops was the second task after establishing the system of soil fertility, temperature, pH, and moisture and pH sensor. Kamatchi et al. [15] propose to use a hybrid approach with a recommender system based on Case-Based Reasoning (CBR) and a predictive analysis in determining the most effective crop to grow under a given weather condition in an attempt to increase the success rate of the system. Certainly, cooperative filtering and CBR are a new hybrid system. One of the peculiarities of this model is that it also applies a hybrid recommender system to examine agricultural data at thelevel of a district, predict further weather, and then suggest crops by that predictions, considering the farming pattern of the district.

Kiruthika et al. [16] introduces a methodology that involves the use of Improved Distribution-based Chicken Swarm Optimisation (IDCSO) coupled with the Weight-based LSTM (WLSTM) to predict and give recommendations on crops with the objective of overcoming the aforementioned problems using the IoT.

The main steps in it are the pre- processing, the selection of attributes through the IDCSO and the prediction of crops through the WLSTM method. The first step to take is the collection of climate facts and then the subsequent step involves the collection of crop production.

According to Dhruvi et al. [17], it was proposed to use a system based on a combination of IoT and ML to conduct soil testing using sensors, which aims at measuring and monitoring soil constraints. The method minimizes chances of soil deprivation and helps to attain crop vitality. This system uses a range of sensors, such as those to measure soil moisture, temperature, pH, and NPK, to measure the corresponding levels of attributes in the soil. Archana et al.

A technique presented by [18] focuses on macronutrients (NPK), electrical conductivity, pH of soil, and temperature in order to provide the best recommendations on crops. The proposed solution creates a support system on crop-rotation, production forecasting, prediction, and fertiliser prescriptions. This study gives a system that uses an agricultural dataset and employs an ensemble technique of classifying using the voting technique to give appropriate crops.

Viviliya B et al. [19] came up with a recommendation model in order to understand the crops that could be grown in a particular climatic environment and geographical area. This study proposes a model of crop referral, which fuses association rules with algorithms like J48, Naive Bayes and so on. They include soil type, NPK ratios, fertiliser, soil pH, organic carbon content and others.

Paul et al. [20], on one hand, provide an approach to predicting the categorisation of the studied records of soil through data mining techniques. The expected type is crop yield. This is a problem of prediction of agricultural yield in the form of a classification rule based on the Naive Bayes and K-Nearest Neighbour algorithms.

Gulati et al. [21] review a number of machine learning approaches to predicting agricultural harvests in India. Then, agricultural data have been subjected to Ml techniques to evaluate the best methodology. Bondre et al.

Predicts and then implements a method of forecasting the agricultural output, using chronological data. This is achieved through the application of machine learning algorithms (SVM and RF) to agricultural data so as to suggest fertilisers that can suit particular crops. The paper will focus on the growth of an extrapolative model to predict future yields in crop growth. This report gives a brief analysis of crop forecasting using machine learning algorithms.

Lakshmi N et al. [23] developed a method of tracking agricultural activity. Some of the factors considered by them include climate, topography, water resources, and land use. The objective was to come up with a system that will predict the type of soil and also recommend the appropriate crops to be grown in the soils. The benefit is that the general crop productivity may be increased. The proposed solution is limited to few crops.

To achieve the goal of crop forecast based on the category methods based on the postulation of the most suitable crop(s) in a certain strip of land, Suruliandi et al. [24] proposed to compare multiple wrapper feature selection methods. The experimental outcome proves that the Recursive Feature Elimination approach coupled with Adaptive Bagging classifier has better performance than the others. Based on the input of soil data, Pandith et al. [25] examined the potential of various ML approaches to estimate the yields of the mustard crop. The

The data that was used to establish the experiment was obtained in Department of Agriculture in Talab Tillo, Jammu. The data entailed the samples of soil used in different districts of mustard crop in the Jammu region. In recent times, most researchers are undertaking the crop recommendation and provided a comprehensive review on various works conducted in the literature [32-37].

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Table.1 Comparison table of various crop recommendations using Machine Learning (ML) algorithms

Ref	Dataset	ML algorithm	Accuracy
8	Kaggle	KNN, DT, RF, XGBoost, and SVM	97.18
9	Kaggle	LR, DT, GNB, SVM, RF, XGBoost, SGD, CBoost	99.15
10	Manual &	RF, CatBoost	97.5
11	Manual	DT, SVM, MSVM	97.3
12	Manual	KNN	99.67
13	Manual	Adaboost, SVM, RF, LR	98
14	Features	FL	--
15	Features	Case based Reasoning, ANN	98.58
16	Kaggle	ANN	95.69
17	Kaggle &	Naïve Bayes, LR, DT, XGBoost, RF	97.34
18	Kaggle &	Voting based Ensemble classifier	98.27
19	Kaggle	Naïve Bayes, DT	95.34
20	Manual	KNN and Naïve Bayes	94.59
21	Kaggle	RF, LR, Gradient Boost, DT	96.46
22	Kaggle	RF, SVM	98.64
23	Manual	Soil Features and Data mining	95.76
24	Manual &	Naïve Bayes, KNN, DT, RF, SVM and Bagging	99.37
25	Huge soil	KNN, Naïve Bayes, ANN, MLR, RF	94.13
26	Manual	LR, DT, NB, RF XGBoost	99
27	Manual and online data	CHAID, RF, NB, KNN	88
28	Socia economical stats	NN, RF, DTKNN	91
29	1530 soil samples	SVM & RF	95.49
30	Features of soil	Naïve Bayes & J48	98.35
31	**Features of soil**	**Gaussian Kernel based SVM, Bagged Tree and Weighted KNN**	**97.24**

3. Methodology for CR using ML Algorithms

The CR expending soil and ecological conditions for various crops are predicted using the standard methodology which is shown in the figure 1 [35].

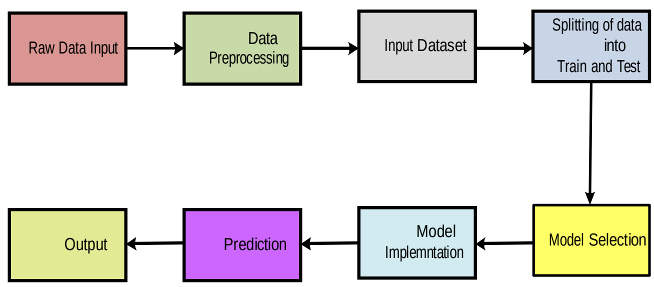

Figure. 1 Methodology for crop recommendations

The block diagram is very clear in terms of the step-by-step procedure of any crop recommendation on the basis of different parameters. The fields which are collected in the form of raw data are subjected to the processing such as the withdrawal of the redundant data. The ML model is first trained with the help of the available datasets of various types of crops with different parameters such as soil and ecological settings. The model is trained in different aspects of consideration of the available data. Choice of user is the ML model selection of the various parameters. The predicted values against the testing data are measured based on different performance measures such as precision, F1-score, accuracy etc.

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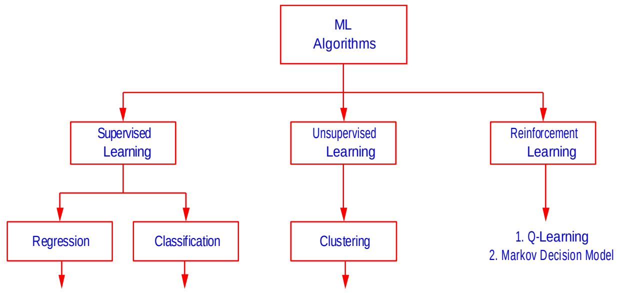

Table. 2 Various ML Algorithms with advantages and disadvantages

ML Model	Description	Advantages	Disadvantages
Regression Models	These used training data to guess what a number will be when it is put into an unknown input. [38-41].	Suitable for low number of datasets, less complex	Overfitting occurs even for small datasets
Random Forest (RF)	This method involves learning to categorise and predict outcomes by aggregating many decision trees during training, ultimately presenting the category that represents the mode of the classifications or the average prediction of the individual trees [40, 41].	Avoids overfitting of data and best estimates the relevance between the features	Most sensitive to data used and complex compared to all models
Decision Tree (DT)	DT is a regression and classification technique that can handle both continuous and categorical inputs and outputs. By looking for the most significant splitter among the independent variables, it partitions the data into two or more similar areas [38-41].	Not required preprocessing to predict the results or for taking decision	More training time and costly
Support Vector Machine (SVM)	SVMs are better at handling high- dimensional data with several predictor variables, and they use class-separated training data to make output predictions [38-41].	Handle structured and unstructured data and predict even with less data	Not suitable for huge datasets, Data points must less than the trained data samples
K Nearest Neighbours (KNN)	It sorts a labelled dataset into groups based on the results it produces [38- 41].	It can handle huge datasets and also works well for noisy data	Must calculate K value for all sample points and complex due to computation of K value
Naïve Bayes (NB)	**These classifiers are a type of probabilistic ML model used to solve classification tasks [38-41].**	**Suitable for large datasets, handles multi class tasks**	**It considers all features are uncorrelated**

Table. 3 Sample Crop Recommendation dataset

Label	N	P	K	Temp	Hum	pH	Rainfall	Elevation	Slope	Aspect	Wind speed	Soil texture	ec	Zinc

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Rice	14	65	45	38.8	10.4	9.6	97.2	2196.3	54.9	West	70.3	Silt	0.1	**97.1**
Potatoes	27	88	3	39.3	4.77	13.2	215.4	1421.7	59.5	North	81.7	Loamy	0.6	**88.8**
Wheat	45	69	51	3.02	51.4	13.7	325.2	72.7	82.3	West	16.3	Silt	0.5	**44.7**
Rice	**28**	**32**	**55**	**20.6**	**59.4**	**13.2**	**355.7**	**2877.5**	**1.51**	**West**	**46.4**	**Silt**	**0.1**	**25.3**

Sample Datasets for Crop Recommendations

There are various types of datasets available for crop recommendations considering different parameters. The data set mainly contains the micronutrients N, P and K called Nitrogen (N), Phosphorus (P) and Potassium (K). Other parameters like temperature, humidity, pH, soil and electrical conductivity (ec) conditions, etc. Few sample data sets are tabulated in table 3 [42].

Performance Metrics

The efficiency of the machine learning models for crop recommendations are observed using various performance metrics, which are formulated below [43-45].

Accuracy, which computes the total correct predictions out of all predictions.

$$Ac = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

Precision calculates the efficiency of predicting positives of the model.

$$Prec = \frac{TP}{TP+FP} \quad (2)$$

Recall shows how well the model can find the actual positives out of all the true positive cases

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F1 Score integrates precision and recall into a singular statistic by calculating their harmonic mean, so offering a fair assessment of a model's efficacy, especially in the context of imbalanced datasets.

$$F1\,Score = 2 * \frac{Prec*Recall}{Prec+Recall} \quad (4)$$

Along with the above measurements, root mean square error (RMSE), mean absolute error (MAE) and coefficient of Determination (r2) are also included in the list of measurements used to determine the effectiveness of the proposed model [46, 47].

4. Conclusions

The paper provided a comprehensive review regarding crop recommendations and prediction with the help of ML Techniques. The ML models that are playing a crucial role in crop recommendation in the recent days. Random Forest (RF), SVM and XGBoost are the algorithm types that are giving impressive prediction scores across different datasets. The effectiveness of such algorithms is tested through such performance metrics as Accuracy, precision and Recall. The RMSE, MAE and 22 metrics were also used to assess the crop prediction by researchers.

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