Crop Prediction Using Machine Learning

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ABSTRACT

Predicting crop yields is crucial to agriculture. There are several variables at play when it comes to crop productivity. The goal of this research is to provide lowcost techniques for forecasting agricultural yields utilizing existing variables like irrigation, fertilizer, and temperature. The five-feature selection (FS) techniques described based on the literature survey in this article include sequential forward FS, sequential backward elimination FS, correlation-based FS, random forest variable importance, and the variance inflation factor algorithm. Machine learning methods are typically well adapted to a particular area, which makes them quite helpful to farmers in predicting agricultural yields. A novel FS method termed modified recursive feature removal can be used to enhance crop forecast (MRFE). The MRFE technique locates and prioritizes a dataset's most critical features with the use of a ranking algorithm

Keyword: —*Machine Learning, Crop prediction, Agriculture, Soil, Environment, Classification*

INTRODUCTION

Although agricultural crop forecasting has recently made progress, it is still a challenging process to complete employing a variety of technology resources, approaches, and procedures. The goal of agricultural management research is to create algorithms that can accurately anticipate crop production using information like irrigation data, fertilizer information, and temperature. The identification of crucial qualities that aid in identifying crops that are suitable for particular land locations is required in order to make use of a big crop prediction data collection. Approaches for feature selection are used in the process. Crop yield can be predicted using weather information and historical crop production data. A crop production dataset might contain variables such as year, area, production, and yield, for example. Weather variables that can be included in a dataset include minimum temperature, maximum temperature, average temperature, precipitation, evapotranspiration, and reference crop evapotranspiration. There may be other variables in a meteorological dataset, but these are the most crucial ones for predicting agricultural yields. Using feature selection algorithms that recognize pertinent paddy field situations, a thorough image of paddy crop output may be obtained (features).

LITREATURE SURVEY

Paper 1: Feature Selection for Yield Prediction Using Boruta Algorithm

In this paper, five-point selection ways are used to pick the features successional forward point selection, successional backward point junking, correlation- grounded point selection, arbitrary timber Variable Importance, and Variance Affectation Factor.

Paper 2: Review on Use of "BAGGING" Technique in Agriculture Crop Yield Prediction

The fashion relies on the conception of comprising several performances of a machine literacy model, each interpretation trained on different bootstrapped data samples. The delicacy of crop yield vaticination will be bettered by using a voting cast of bagging fashion with different parameters.

Paper 3: Recursive feature elimination in random forest classification supports nanomaterial grouping

The reduced RF model following backward RFE had the stylish performance in terms of balanced delicacy of the vaticination model. In every illustration, variable selection grounded on the MDA produced equal or better issues than Gini significance.

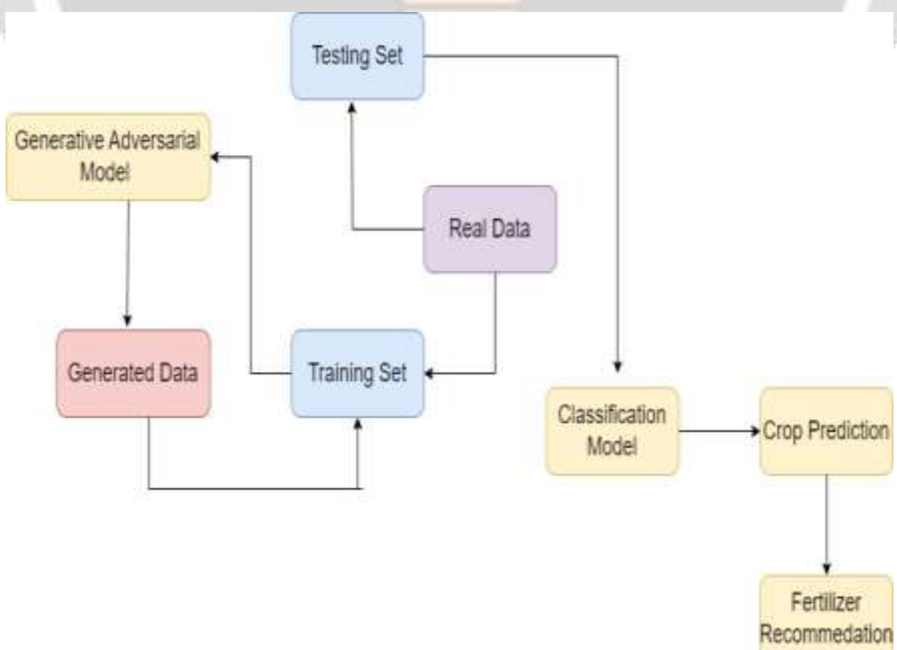
Paper 4: FEATURE SELECTION FOR YIELD PREDICTION USING BORUTA ALGORITHM

In this paper, The Boruta algorithm was used to elect the most essential features for crop yield vaticination. Crop area, conduit length, number of open wells, number of tube wells, number of tanks, maximum temperature, average temperature, nitrogen, phosphorus, and potash diseases, sun radiation, and seed rate have all been linked as essential factors

Paper 5: An Ensemble of Heterogeneous Incremental Classifiers for Assisted Reproductive Technology Outcome Prediction.

The new miscellaneous incremental classifier is known as IB1- A1DE. The methodology was created primarily to directly prognosticate ART issues. To estimate the model's efficacity, several data sets of ART and several different test choices are used.

PROPOSED SYSTEM



System Architecture

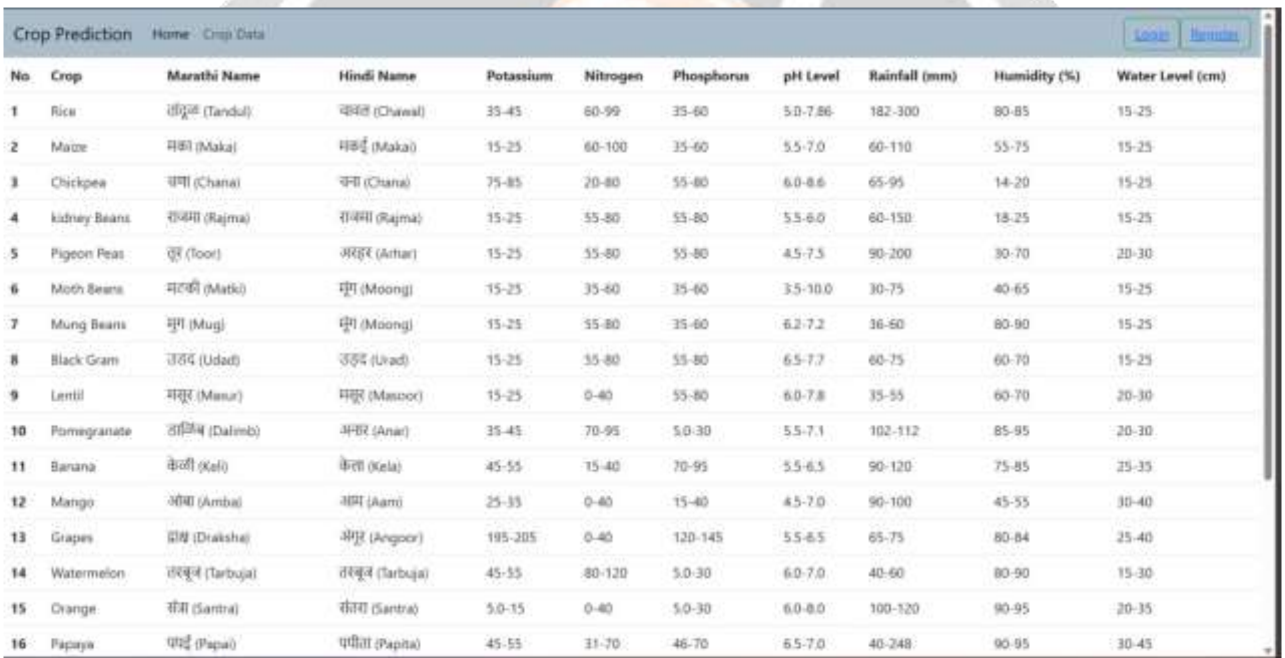
The MRFE approach is especially beneficial in agriculture. Accurate agricultural production prediction can assist governments and authorities in making strategic policy decisions, as well as farmers. The emphasis on increasing

production without addressing the environmental implications of input resources has resulted in environmental degradation. The MRFE technique identifies the most appropriate crop properties for prediction.
The proposed MRFE includes eight soil properties (N, P, K, Zn, Cu, Fe, Mn, and EC) and two climate parameters (seasons and rainfall). N, P, and K are soil macronutrients that help in crop growth and quality. Zn, Cu, Fe, and Mn are soil micronutrients that aid in photosynthesis and respiration.

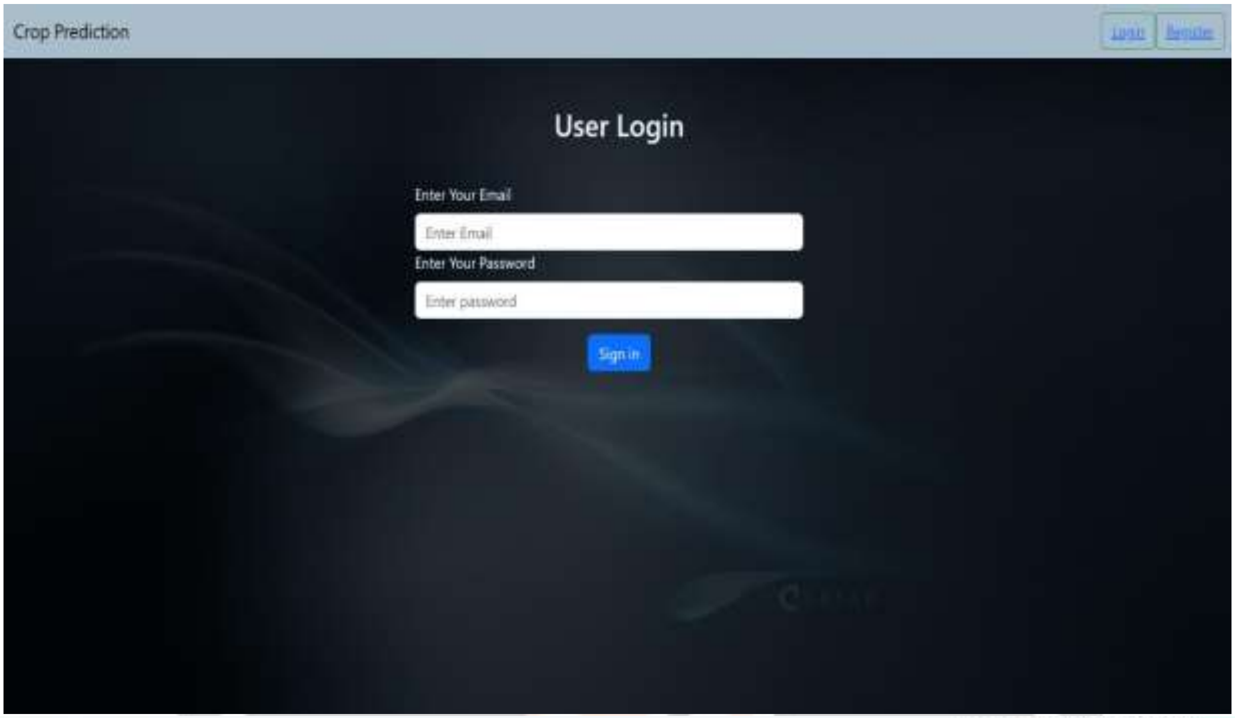
1. **Random Forest:**

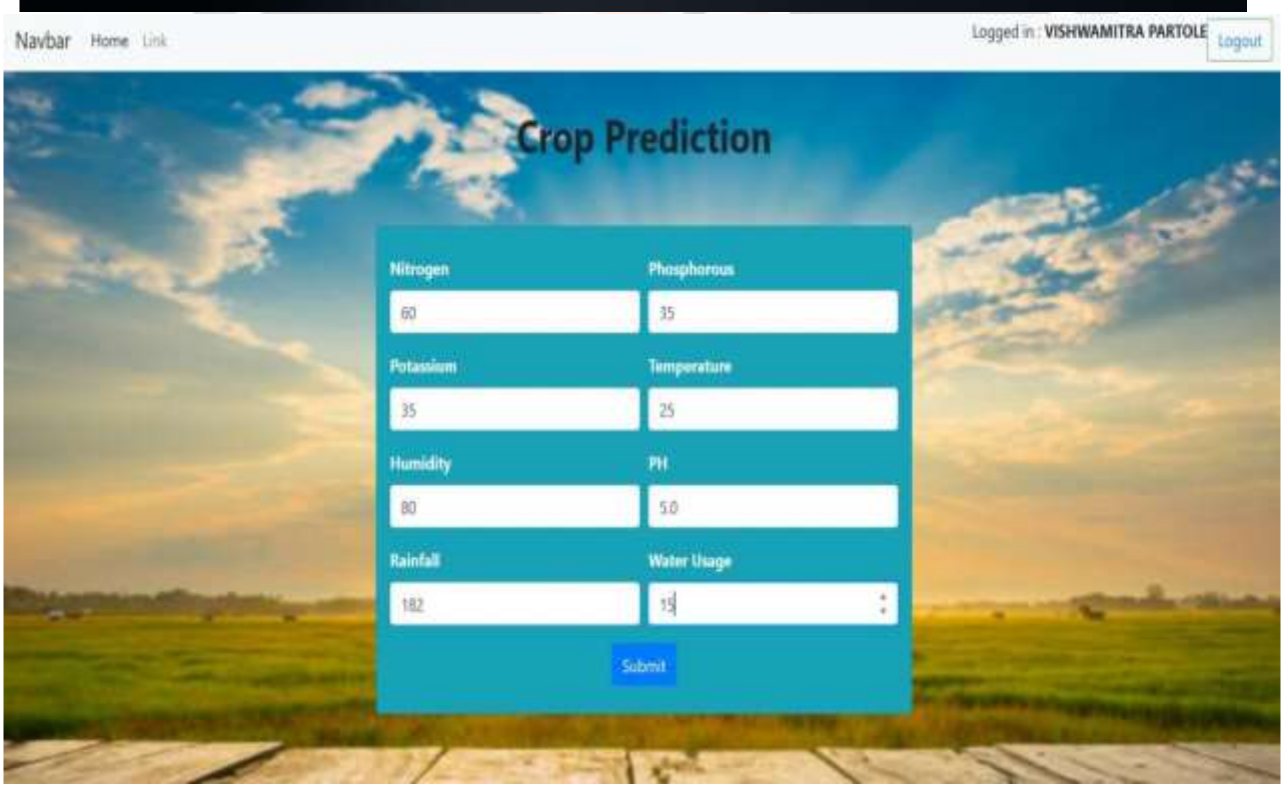
Random forests are a machine learning algorithm. The basic premise of the algorithm is that building a small decision-tree with few features is a computationally process. The algorithm works as follows: for each tree in the forest, we select a bootstrap sample from S where S (i) denotes the ith bootstrap. We then learn a decision-tree using a modified decision-tree learning algorithm. The algorithm is modified as follows: at each node of the tree, instead of examining all possible feature-splits, we randomly select some subset of the features f $\in$ F:Where, F is the set of features. The node then splits on The best feature in f rather than F. In practice f is much,Much smaller than F. Deciding on which feature to split is oftentimes the most computationally expensive aspect of decision tree learning. By narrowing the set of features, we drastically speed up the learning of the tree.

Result


Crop Prediction Home Crop Data

No	Crop	Marathi Name	Hindi Name	Potassium	Nitrogen	Phosphorus	pH Level	Rainfall (mm)	Humidity (%)	Water Level (cm)
1	Rice	तांदूळ (Tandul)	चावल (Chawal)	35-45	60-99	35-60	5.0-7.86	182-300	80-85	15-25
2	Maize	मका (Maka)	मकई (Makai)	15-25	60-100	35-60	5.5-7.0	60-110	55-75	15-25
3	Chickpea	चणा (Chana)	चना (Chana)	75-85	20-80	55-80	6.0-8.6	65-95	14-20	15-25
4	kidney Beans	राजमा (Rajma)	राजमा (Rajma)	15-25	55-80	55-80	5.5-6.0	60-150	18-25	15-25
5	Pigeon Peas	तूर (Toor)	अरहर (Arhar)	15-25	55-80	55-80	4.5-7.5	90-200	30-70	20-30
6	Moth Beans	मटकी (Matki)	मूंग (Moong)	15-25	35-60	35-60	3.5-10.0	30-75	40-65	15-25
7	Mung Beans	मुग (Mug)	मूंग (Moong)	15-25	55-80	35-60	6.2-7.2	36-60	80-90	15-25
8	Black Gram	उडद (Udad)	उड़द (Urad)	15-25	35-80	55-80	6.5-7.7	60-75	60-70	15-25
9	Lentil	मसूर (Masur)	मसूर (Masoor)	15-25	0-40	55-80	6.0-7.8	35-55	60-70	20-30
10	Pomegranate	डाळिंब (Dalimb)	अनार (Anar)	35-45	70-95	5.0-30	5.5-7.1	102-112	85-95	20-30
11	Banana	केळी (Keli)	केला (Kela)	45-55	15-40	70-95	5.5-6.5	90-120	75-85	25-35
12	Mango	आंबा (Amba)	आम (Aam)	25-35	0-40	15-40	4.5-7.0	90-100	45-55	30-40
13	Grapes	द्राक्ष (Draksha)	अंगूर (Angoor)	195-205	0-40	120-145	5.5-6.5	65-75	80-84	25-40
14	Watermelon	टरबूज (Tarbuja)	तरबूज (Tarbuja)	45-55	80-120	5.0-30	6.0-7.0	40-60	80-90	15-30
15	Orange	संत्रा (Santra)	संतरा (Santra)	5.0-15	0-40	5.0-30	6.0-8.0	100-120	90-95	20-35
16	Papaya	पपई (Papai)	पपीता (Papita)	45-55	31-70	46-70	6.5-7.0	40-248	90-95	30-45


Crop Prediction
User Login
Enter Your Email
Enter Email
Enter Your Password
Enter password
Sign in


Navbar
Home
Link
Logged in : VISHWAMITRA PARTOLE
Logout
Crop Prediction
Nitrogen
60
Phosphorous
35
Potassium
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Temperature
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Humidity
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PH
5.0
Rainfall
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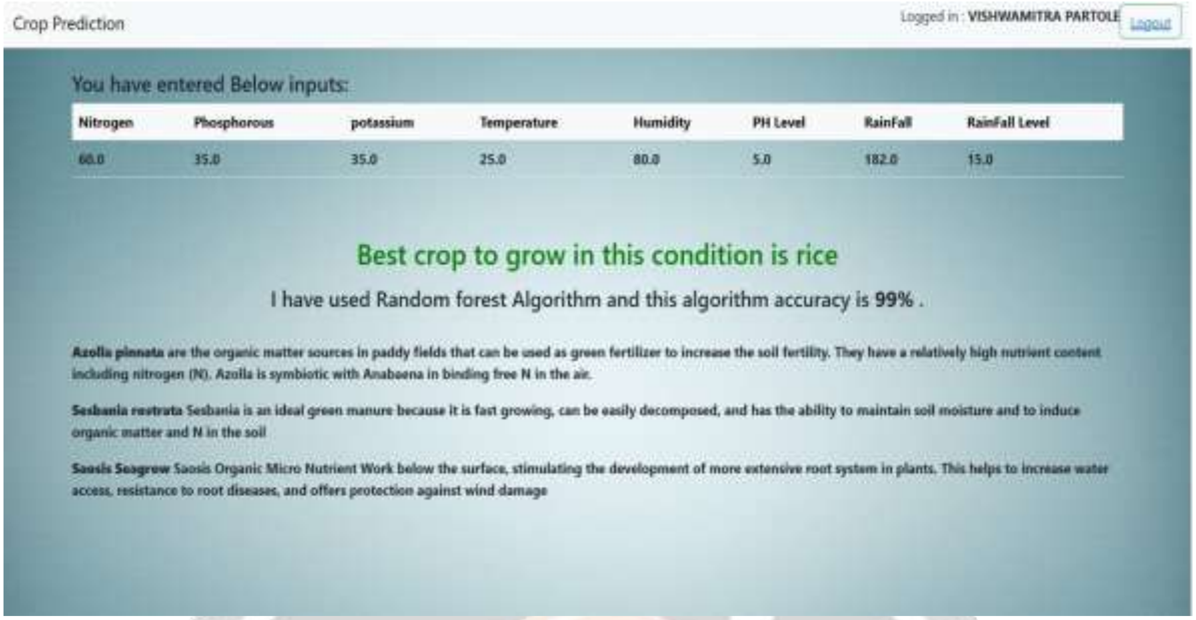
Water Usage
15
Submit



CONCLUSION

The MRFE approach put out in this study can be used with data sets from both crop and non-crop sources. The MRFE employs permutation and ranking to choose the traits with the best prediction ACC in the least amount of time as compared to earlier methods. MRFE approach for applying classification algorithms to identify the best crops for farming

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