

CROP PREDICTION BASED ON CHARACTERISTICS OF THE AGRICULTURAL ENVIRONMENT USING VARIOUS FEATURE SELECTION TECHNIQUES AND CLASSIFIERS

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ABSTRACT

Agriculture plays a vital role in ensuring food security and economic sustainability, making accurate crop prediction essential for maximizing agricultural productivity and resource utilization. The selection of suitable crops depends on various environmental factors such as soil characteristics, temperature, humidity, rainfall, nutrient content, and climatic conditions. Traditional crop selection methods often rely on farmer experience and manual assessment, which may not always result in optimal agricultural outcomes. This paper presents a crop prediction framework based on the characteristics of the agricultural environment using various feature selection techniques and classifiers. The proposed approach utilizes agricultural datasets containing environmental and soil parameters to identify the most influential features affecting crop growth and yield. Feature selection techniques are employed to reduce data dimensionality and improve model efficiency, while multiple machine learning classifiers are used to predict the most suitable crop for a given agricultural environment. Experimental analysis demonstrates that the integration of feature selection methods with advanced classification algorithms enhances prediction accuracy, improves computational efficiency, and supports informed decision-making in precision agriculture. The proposed framework provides an intelligent and scalable solution for sustainable crop planning and agricultural resource management.

1. INTRODUCTION

Crop prediction in agriculture is a complicated process [1] and multiple models have been proposed and tested to this end. The problem calls for the use of assorted datasets, given that crop cultivation depends on biotic and abiotic factors [2]. Biotic factors include those elements of the environment that occur as a result of the impact of living organisms (microorganisms, plants, animals, parasites, predators, pests), directly or indirectly, on other living organisms. This group also includes anthropogenic factors (fertilization, plant protection, irrigation, air pollution, water pollution and soils, etc.). These factors may contribute to the occurrence of many changes in the yield of crops, cause internal defects, shape defects and changes in the chemical composition of the plant yield. The shaping of the environment as well as the

growth and quality of plants is influenced by abiotic and biotic factors. Abiotic factors can be divided into physical, chemical, and other. The recognized physical factors include: mechanical vibrations (vibration, noise), radiation (e.g., ionizing, electromagnetic, ultraviolet, infrared); climatic conditions (atmospheric pressure, temperature, humidity, air movements, sunlight); soil type, topography, soil rockiness, atmosphere, and water chemistry, especially salinity. The chemical factors include: priority environmental poisons, such as sulfur dioxide and derivatives, PAHs; nitrogen oxides and derivatives, fluorine, and its compounds, lead and its compounds, cadmium and its compounds, nitrogen fertilizers, pesticides, carbon monoxide. The others are: mercury, arsenic, dioxins and furans, asbestos, and aflatoxins [3]. Abiotic factors also include

bedrock, relief, climate, and water conditions - all of which affect its properties. Soil-forming factors have a diversified effect on the formation of soils and their agricultural value [4].

Predicting crops yields is neither simple nor easy. The methodology for predicting the area under cultivation is, according to Myers *et al.* [5] and Muriithi [6], a set of statistical and mathematical techniques useful in an evolving and improving optimization process. It also has important uses in design, development, and formulation new as well as improving existing products. Presentation or performance of statistical analysis requires the possession of numerical data. Based on them, conclusions are drawn as to various phenomena and further, on this basis, binding economic decisions can be made. According to Muriithi [6], the better you describe certain phenomena in terms of numbers, the more you can say about them, and with increasing data accuracy you can also obtain more accurate information and make more accurate decisions.

The biggest problem in the temperate climate zone is assessment of agro climatic factors in terms of shaping the yield of winter plant species, mainly cereals. The key factor influencing wintering yield, which provides access to days with a temperature over of 5°C, their number and frequency, and the number of days in the wintering period with temperatures above 0°C and 5°C. A number of these can be estimated on the basis of public statistics and yield regression statistics in years. Developed models for checking the situation that assess whether they want to be a probation of state policy in the field of intervention in the cereal market. Efficient forecasting of productivity requires forecasting of agro meteorological factors. Aspects related to the variability of these factors may pose a particular

problem [7]. Many researchers have dealt with this issue with varying degrees of success [8]_[10].

Grabowska *et al.* [9] predicted narrow-leaf lupine yields for 2050-2060 using weather models and three climate change scenarios for Central Europe: E-GISS model, HadCM3 and GFDL. The t of the models was assessed by means of the determination coefficient R^2 , corrected coefficient of determination R^2_{adj} , standard error of estimation and the coefficient of determination R^2_{pred} calculated using the Cross Validation procedure. The selected equation was used to forecast lupine yield under the conditions of doubling the CO₂ content in the atmosphere. These authors stated that the influence of meteorological factors on the yield of narrow-leaved lupine varied depending on the location of the station. The temperature (maximum, average, minimum) at the beginning of the growing season, as well as rainfall during the $_{owering}$ - technical maturity period, most often had a significant influence on the yield. It has been shown that the predicted climate changes will have a positive effect on the lupine yield. The simulated probability was higher than observed in 1990-2008, and HadCM3 was the most favorable scenario.

Dłubrowska-Zielińska *et al.* [8] assessed the usefulness of plant biophysical parameters, calculated from the ranges of rejected electromagnetic radiation recorded by the new generation satellites Sentinel-2 and Proba-V, for forecasting crop yields in Poland. In 2016-2018, ground measurements were carried out in arable fields in the area included in the global crop monitoring network GEO Joint Experiment of Crop Assessment and Monitoring JECAM. Classification of crops was performed using optical and radar images Sentinel-1 and RadarSat-2. The prototypical model of Biomass

and Evapo transpiration PRO was used to simulate the growth of winter wheat cultivation, to forecast its biomass size. Got high accuracy of 94% of the size of biomass modeled with real biomass.

2. LITERATURE SURVEY

Rice Yield Prediction Using Support Vector Machines, 2019. Support vector machines (SVMs) are now widely used in the world of computer software. Because they can reproduce, they are often employed inside the provision. The development of SVM-primarily based category fashions for Indian rice yield prediction is the focus of this work. The kernel polynomial function of SVM education, okay-cross validation, and the multiple classification technique have all been used in experiments. The Department of Economics and Statistics of the Indian Department of Agriculture provided data on rice output in India for this study. The four-triple cross-validation method produced a great predicted accuracy of 75.06% for the four-year relative average growth. MATLAB software is utilized in this work's experiments.

The protection of American agriculture's food supply and economic growth are significantly aided by agricultural coverage. One of the main challenges in agricultural planning is selecting the crop or crops to plant. It is dependent on a number of factors, such as government coverage, market pricing, and production pace. Numerous scholars have examined crop forecasting, climate forecasting, soil classification, and crop class in order to inform agricultural planning through the application of statistical techniques or system learning approaches. Crop selection becomes a conundrum when there are multiple options for

when to plant and use available land. In order to solve the crop selection problem, optimize crop internet at a certain time in the yield duration, and ultimately obtain the greatest financial increase of the location, this study employs a technique known as the Crop Selection Method (CSM).

Machine Learning Crop Data System, 2020. As far as we know, India is the second most famous country in the United States. The majority of people in India and around the world work in agriculture. Farmers repeatedly plant the same plants without experimenting with other crop varieties, and they apply fertilizers in unknown amounts without knowing enough about the type and quantity of the fertilizer. As a result, it simultaneously affects yield, causes soil acidity, and damages the top layer. As a result, we developed a system that uses device learning algorithms to raise farmers' productivity levels. Based solely on soil composition and meteorological factors, our method will suggest the greatest crop that is appropriate for a certain soil. The gadget also provides information on the type and quantity of fertilizers needed for seed cultivation. Therefore, farmers may cultivate novel plant varieties, increase yields, and prevent soil pollution by using our equipment.

Give an overview of the usage of machine gaining knowledge of strategies, 2019. In India, one of the most important yet lowest paid jobs are agriculture. By cultivating the most desirable crops, machine learning could change the profitability situation and spur an increase in agriculture. The goal of this paper is to provide a yield prediction through the application of several system study techniques. The mean absolute errors

are used to compare the overall performance of those approaches. Farmers will be able to choose which crop to grow in order to maximize yield with the help of machine learning algorithms that consider variables such as area, temperature, rainfall, and more.

3. EXISTING SYSTEM

You *et al.* [15] posited an adaptable and precise technique to anticipate yields by employing openly accessible remote sensing data.

The methodology enhances existing procedures in three different ways. To begin with, a remote detecting network is applied to propose a working methodology. Next, a novel dimensionality reduction procedure is presented that uses a convolutional neural network (CNN) alongside long-term memory. Finally, a Gaussian process is used to investigate and examine the spatio-transient structure of the data and enhance its accuracy. Anantha *et al.* [16] implemented a recommendation system using an associate ensemble model with majority voting. The random tree, Chi-square Automatic Interaction Detection (CHAID), kNN, and Naive Bayes (NB) are used as learners to help determine the most appropriate crop, taking into consideration soil parameters, with the results showing high accuracy and potency. The classified image generated by these techniques consists of ground truth-applied mathematics information. Further, it incorporates such data as the parameters of the square measure in terms of the weather and crop yield, as well as state and district-wise crop produce.

All of the above are employed to predict specific crop yields in a given set of circumstances. Rale *et al.* [17] developed a forecasting model which uses the default settings along with RF regression for crop yield production.

Fernando *et al.* [19] studied data on annual coconut production from 1971 to 2001 in a particular region and assessed its economic impact. The research revealed that the loss sustained by the economy in crop shortage terms was around US \$50 million. Ji *et al.* [20] advanced an estimation technique to predict rice yields. The study attempted to determine the effectiveness of artificial neural networks (ANN) in predicting rice yield in mountainous regions. It assessed the efficacy of the ANN, relative to biological parametric variations, and compared the efficiency of multiple bilinear regression models with the ANN model. Boryan *et al.* [21] proposed a decision tree-based technique to depict openly accessible state-level crop cover groups, in accordance with guidelines laid down by the Cropland Data Layer (CDL) and National Agricultural Statistics Service (NASS), and utilizing ground truth collected during the June Agricultural Survey. The proposed work outlines the NASS CDL program.

It presents information dealing with handling strategies, order and approval, precision evaluation, and CDL item particulars, and product cost estimation procedure. Hansen and Loveland [22] proposed the use of Landsat to acquire satellite imagery that facilitates remote sensing of the environment.

Disadvantages

- ❖ The system is not implemented RECURSIVE FEATURE ELIMINATION (RFE).
- ❖ The system is not implemented Sampling techniques which are applied during preprocessing to balance the dataset and maximize the prediction performance.

4. PROPOSED SYSTEM

• Boruta is a random forest-based classification algorithm [38] that involves the voting of versatile unbiased indistinct classifiers in decision trees. The importance of a characteristic is estimated by calculating the loss of classification exactness caused by the random permutation of attributes within objects. The average and standard deviation of the loss of accuracy are calculated, and the average loss is divided by the standard deviation to obtain the Z score to measure average fluctuations in mean accuracy loss among crops.

A 'shadow' attribute is made for each tree by randomly rearranging the values of the initial attributes across objects. The importance of every attribute is determined by analyzing all the attributes in the system. Given the random nature of the fluctuations, the shadow attributes are used as a reference to point to the most important ones. As is to be expected, the degree of accuracy depends greatly on the shadow attributes. Consequently, the values will be re-shuffled constantly to obtain optimal results.

The Boruta algorithm comprises the following steps: 1. The data system, which is extended by affixing copies of all the shadow attributes, is always prolonged by 5 shadow attributes.

2. The added attributes are shuffled with the original attribute to remove any correlation with the response.

3. The Z score is computed by running a random forest algorithm on the widespread information system.

4. The Maximum Z Score Attributes (MZSA) are calculated and any attribute with a value higher than the MZSA is assigned a 'hit'.

5. For attributes with undetermined importance, a two-sided test of equality with the MZSA is carried out.

6. Attributes with importance significantly lower than the MZSA are identified as 'unimportant' and permanently eliminated from the information system.

7. Attributes with importance significantly higher than the MZSA are marked 'important'.

8. Shadow attributes are thus eliminated from the information system.

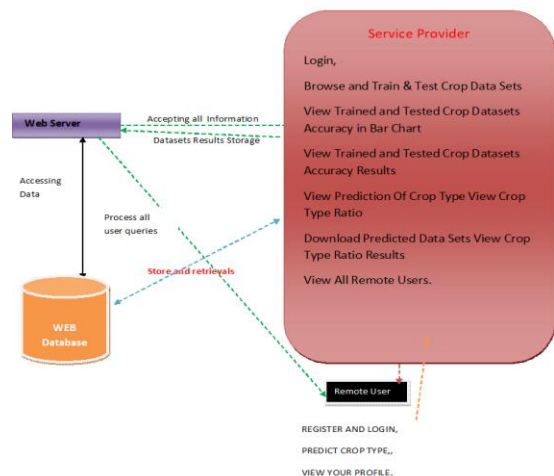
9. The process is repeated until all attributes are marked with a level of importance.

Advantages

- The RFE technique is a wrapper feature selection technique that starts with the entire dataset. The ranking method crucial to the RFE technique orders the dataset from the best to the worst, based on which salient features are selected.
- The main advantage the RFE has over other methods is that it categorically verifies every feature's role in processing the output of the model and eliminates features only based on their performance.

5. SYSTEM ARCHITECTURE

Architecture Diagram



6. MODULES

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Browse and Train & Test Crop Data Sets, View Trained and Tested Crop Datasets Accuracy in Bar Chart, View Trained and Tested Crop Datasets Accuracy Results, View Prediction Of Crop Type ,View Crop Type Ratio, Download Predicted Data Sets, View Crop Type Ratio Results, View All Remote Users.

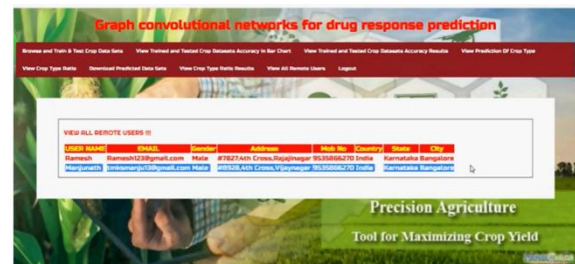
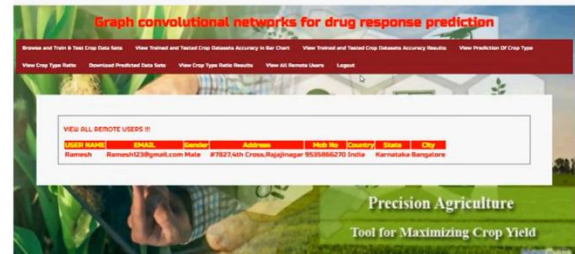
View and Authorize Users

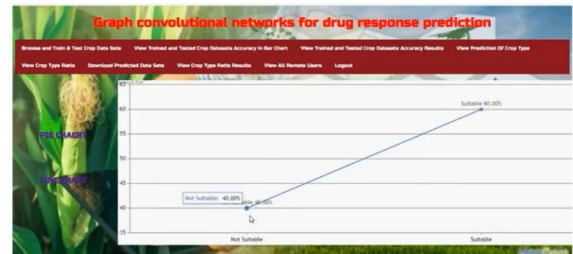
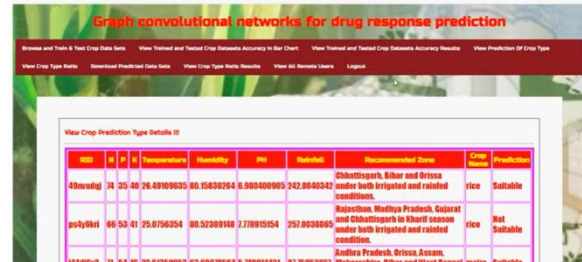
In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT CROP TYPE, VIEW YOUR PROFILE.

7. RESULTS





8. CONCLUSION

This study presented a machine learning-based crop prediction framework that utilizes agricultural environmental characteristics, feature selection techniques, and classification algorithms to identify suitable crops for cultivation. The proposed approach effectively analyzes factors such as soil properties, climatic conditions, and environmental parameters to support data-driven agricultural decision-making. By applying feature selection methods, the framework identifies the most relevant attributes influencing crop growth while reducing data complexity and improving model performance. Experimental observations indicate that machine learning classifiers achieve high prediction accuracy and provide reliable recommendations for crop selection across diverse agricultural environments. Furthermore, the integration of feature selection techniques enhances computational efficiency and

contributes to more robust predictive modeling. The proposed framework supports precision agriculture practices, improves resource utilization, and assists farmers in maximizing crop productivity and profitability. Future research may focus on incorporating deep learning models, remote sensing data, Internet of Things (IoT)-based agricultural monitoring systems, and real-time environmental analytics to further improve crop prediction accuracy and sustainable farming practices.

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