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The new machine learning feature selection method used in fertilizer recommendation

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ABSTRACT

Fertilizer recommendation is the crucial factor to be considered in automation of agricultural predictions. Fertilizer fill the necessary portion of any farming region. There are some micronutrients and macro nutrients which need to be given to crops for proper growth. If fertilization is not done to an optimum level, it may badly harm the soil quality and crop health ,so optimum fertilization is important. In this paper we discuss fertilizer and nutrient recommender, where we have used a new feature selection methodology. We have shown the difference between two implementation cases considering presence and absence of feature ranking and selection. Feature ranking and selection has clearly increased the efficiency of the fertilizer & nutrient recommender in our work from 85% to 98%. Feature selection & raking has been introduced with random forest approach.

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1. INTRODUCTION

For the majority of rural Indians, agriculture remains the main source of income and the largest economic sector. Even though the agricultural sector in India has experienced tremendous change, much more work has to be done to improve agricultural practises and raise crop yields through the application of more advanced, scientific techniques. Numerous studies are carried out in the subject of agriculture every day. Farmers continue to be against the adoption of contemporary agricultural practices because they find it difficult to adjust to the new practices [1], [2]. If contemporary farming methods can be implemented more rapidly and affordably, then more farmers will be adopting them instead of the more traditional ones. Not only does agriculture support the economy, but it also supplies consumers with food and the raw resources that industries require to operate. Enhancing agricultural practices is essential given the growing global demand for food.

A number of factors contribute to low crop yield such as inadequate soil fertility, unhealthy soil, a lack of knowledge about pesticides and fertilizers, a lack of understanding of the characteristics of the soil, and a lack of actions necessary to improve the quality of the soil [1], [2].

Soil contains a wide range of macro and micronutrients in their natural forms, such as iron, manganese, copper, sulfur, phosphorus, nitrogen, and potassium (NPK). Numerous factors, including pH, humidity, temperature, monsoon cycles, rainfall, and soil type, are also required for any particular crop to develop in the soil [3]–[6]. The lack of even one nutrient can cause crops to grow abnormally.

Farmers find it challenging to adapt to the technology of today. Costs and using modern technologies are two things that worry farmers a lot. Knowledge of the soil, crops, and soil health would help farmers carry out agricultural practices more efficiently and smoothly. Crop yield and income will rise if the farmer is encouraged to plant the right crops and apply the appropriate amounts of fertilizer [7], [8]. Farmers will benefit from artificial intelligence and machine learning (ML) tools in this area. These challenges will have time and money-saving solutions because of ML techniques [9]–[12].

This study looked at building a 'soil fertilizer recommendation module' using the 'bootstrap aggregation method'. A 'fertiliser recommender' is part of our "soil fertility and crop friendliness detection and monitoring using artificial intelligence (AI) system, which is discussed in the work's methodology section. To predict the right amount of fertilizer and nutrients to use, we use a ML technique called 'bootstrap aggregation'. Rather than merely categorizing the type of fertilizer needed for a particular crop, our recommender system will also get the customized fertilization report for each soil sample that is submitted. The results of this work for proposing nutrients and fertilizers together with their quantities are the most accurate and successful when compared to other systems. The fertilization is an important task carried on in the process of agriculture. Without fertilization soil will not have balanced nutrition to grow the crops. The right amount of fertilization will always be beneficial to maintain soil health. The ML process has shown greater success in the field of agricultural research, fertilizer recommendation also can be employed using ML models [13]–[22].

'Feature selection' is the process of choosing a subset of features from the original features with the goal of minimizing the feature space as much as feasible. To train the perfect model, we must take care to use only the most crucial features. If there are too many features, the model can detect trivial patterns and learn from noise. Not every attribute is used to train a model. Because linked and non-redundant features may help us improve our model, feature selection is important. It also helps to expedite the training process, simplify the model and minimize its complexity, improve accuracy, precision, and recall measures, and make the model easier to understand. If the appropriate characteristics are used for ML model training, the curse of dimensionality can also be avoided.

The process of creating ML models involves feature 'ranking and selection'. Including irrelevant characteristics in the training set reduces the accuracy of the model. In order to improve the effectiveness of the suggested strategy, we have worked on feature ranking and selection. When feature ranking is completed, model accuracy rises. We introduce the new feature ranking method technique. This paper explains the algorithm's specifics and presents fertilizer results with and without feature ranking and selection.

2. RELATED WORK IN FEATURE SELECTION

Crop productivity is increased by accurate crop forecasts. Here, crop prediction is greatly aided by ML. The soil, topographical, and climatic factors all affect the yield prediction. A key component of employing trait selection techniques for forecasting is choosing the proper traits for the right crops. Using classification strategies appropriate for the yield suitable for the land, a comparative study of several selection methods for the coil properties was done for yield prediction in this work. The recursive feature elimination strategy with adaptive bagging classifier is superior to other methods, according to experimental results [23].

Genome-wide single nucleotide polymorphism (SNP) datasets can be processed using supervised ML algorithms. This is frequently not the best solution, though, as the curse of dimensionality causes an overfitted predictive model and lengthy training times. Consequently, it is crucial to choose the most relevant SNPs in order to reduce the total feature count to a more manageable level before training the model. Consequently, the authors put forth that employing a hybrid or two-stage strategy ought to be regarded as "best practice." To decrease the number of candidate SNPs to a manageable level in a hybrid approach, a filter method is typically performed in the first step. This allows for the application of more complex and computationally intensive wrapper, embedding, or exhaustive search methods. The chosen filter should be multivariate and capable of identifying feature interactions, depending on the resources that are available [24].

Feature selection is a dimensionality reduction strategy that selects a subset of the original characteristics that are useful by eliminating features that are redundant, irrelevant, or noisy. Better learning outcomes, such as increased learning accuracy, reduced computational costs, and improved model interpretability, are typically the result of feature selection. A wide range of feature selection algorithms have been presented recently by researchers in computer vision, text mining, and related fields, and their efficacy has been demonstrated through experiments and theory. This paper's goal is to examine these tactics' current state. Furthermore, a thorough experiment is conducted, including some of the techniques reported in the literature, to find out if feature selection can improve learning performance. The study's findings demonstrate the advantages of supervised ML [25].

In this review, the authors have presented a survey of the most current feature selection techniques and their categorization. The authors have discussed some fundamental algorithms of each category. Critical analysis and comparison have been conducted to reveal the advantages and disadvantages of each FS method. an empirical study to evaluate six feature selection methods: RatlifF and IG as filters, feature selection method SFS, feature selection method RFESVM as wrapper, feature selection method least absolute shrinkage and selection operator (LASSO), feature selection method RIDGE as embedding have been conducted. Each method is evaluated in conjunction with two well-known classifiers support vector machines (SVM) and random forest (RF) to reliably test their ability to pick the best subset. The results clearly demonstrate that too much information doesn't always help ML algorithms because it implies that feature subset may contain redundant or irrelevant features and their presence can degrade the classifier's performance [26].

In their paper, Vandermeeren *et al.* [27] proposed a method to systematically generate a set of ML-based pedometers using the Bhattacharyya coefficient to identify features that might be useful for step counting, and proposed three ways to rank the features and a selection method that uses these rankings to determine the features to use according to the pedometer. To illustrate the potential of the proposed algorithm, authors compared different ML algorithms using features selected for accuracy. The accuracy achieved by different combinations of the ML algorithm and ranking approach is promising: compared to state-of-the-art algorithms configured for our evaluation set, the algorithm achieved similar performance. The performance of these state-of-the-art algorithms degrades significantly if not properly configured, while the ML algorithms considered in this paper can easily handle changing situations [27].

Feature selection gains prominence, particularly in datasets that contain a large number of variables and features. By doing this, pointless variables are eliminated, increasing classification efficiency and accuracy. It has been demonstrated that RF is a rather helpful algorithm that can manage the selection problem even when there are more variables. The experiment in this study is carried out by the authors using three widely used data sets with a greater number of variables (bank marketing, automobile appraisal database, and human activity detection in cellphones). The selection of features is done for four basic reasons. Reducing the number of parameters in the model first simplifies it, which in turn shortens training time, improves generalization to lessen overfitting, and avoids the dimensionality curse. Furthermore, the efficacy and precision of every classification model, including RF, SVM, k-nearest neighbors (K-NN), and linear discriminant analysis, are demonstrated. The best classifier is the model with the highest accuracy. In actuality, this paper selects the critical characteristic for classification using RF [28].

3. METHOD

Our study project, "soil fertility and crop friendliness detection and monitoring system using AI," includes the recommendation of fertilizer [29]–[31]. The block diagram is displayed in Figure 1. The soil fertility rate, yield, and recommended crops for that soil are all determined by ML approaches. Following the recommendation of the perfect crops, the optimum fertilizer or nutrients required for the recommended crops are also advised. All forecast findings can be kept in the cloud, and advice reports are given to farmers in a format they can readily read and comprehend.

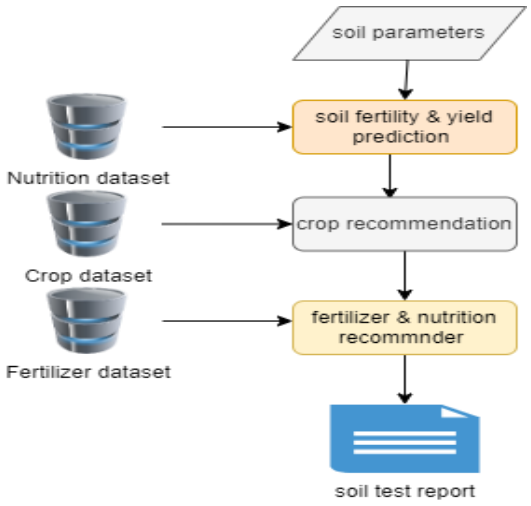

Figure 1. Soil fertility and crop friendliness detection and monitoring system using AI

Fertilization must be adequate in quantity or else it will have a negative impact on the quality of 'soil and crop' health. 'Nutrition recommender' is meant for giving the optimum levels of all the fertilizers and nutrients in combination in kilograms per hectare of land. For the crops that are suggested based on the soil features the fertilizer combination with optimal levels are recommended. Hence customized report is the unique feature of this fertilizer recommender system. Also, organic manure quantity is suggested.

The 'nutrition recommender' module employs the 'bootstrap aggregation' technique, which generates the result by combining several base models or sub models. Every sub model is a "decision tree (DT)". Each sub model (DT) in the system is trained using a different sample from the nutrition dataset since all the sub models in the system receive the reshuffled fraction of the samples. A chunk or some samples of training data from the 'nutrition dataset' are given to each DT. The samples from one sub model might match or might not match those from another sub model. The bootstrap method is the name of this procedure.

All the 'DT' generate an output that will be merged each time a new fertilizer value should be predicted or a test set of data needs to be confirmed. As a result, the aggregate of all the predictions determines the final forecast value; this procedure is called aggregation. The general method of training several sub models and averaging the results is called 'bootstrap aggregation'. Consequently, the recommender system uses random forest trees to build an ensemble model. Figure 2 provides an illustration of this.

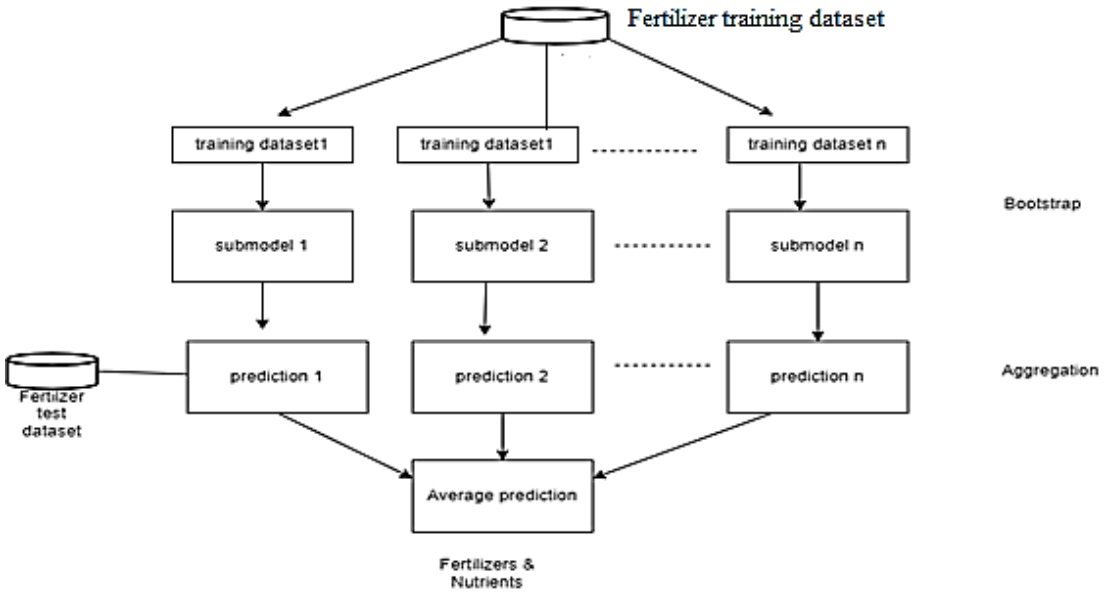

Figure 2. Bootstrap aggregation method used in fertilizer recommender module

More than just a list of fertilizer types is included in the suggested fertilizer. Since we require combinations of fertilizers and their quantities, 'multioutput regressions' are employed to derive the forecasts of continuous dependent variables from number of independent soil parameters. For example, each DT regression predicts the "DAP" value if the model is meant to identify the optimal amount of "DAP" fertilizer for a given soil sample. The average of all the predicted values is then extracted and given to the farmer as a single final "DAP" number. The "overfitting problem" in ML originates from the fact that certain regression models perform well when trained with a dataset but badly when evaluated with new data or when generating predictions. The same technique works well for estimating the quantity of other fertilizers as well. Since each sub-model in the 'bootstrap aggregation' is trained using random data, the overfitting issue can be resolved.

There are several advantages to both the bootstrap aggregation approach and the ensemble methodology. Any system's performance turns out to be its most important element. Because the ultimate forecast in the ensemble technique is the average of multiple estimates, high performance can be expected. The variation can be reduced and the overfitting problem is fixed. 'RF' is supposed to be resistant against outliers and capable of handling very nonlinear datasets.

The required packages and libraries are loaded in our colab file. The 'nutrition recommender' module is implemented on the Colab platform, and the 'nutrition dataset' is read into our colab file. To improve system accuracy and place data on a standard scale, it is normalized. Later, the parameters for the

input and target are set. 'Regression models' are performed and the data is fitted to the model after the data is split into training and testing portions. We forecast, create and evaluate assessment measures, and display the outcomes graphically. The model's efficacy is evaluated using the mean squared error and R2 score values.

3.1. Fertilizer recommendation with new feature ranking technique

The process of selecting a subset of features from the original features to minimize the feature space as much as possible can be called feature selection. We must be careful to employ only the most important features to train an ideal model. The model can learn from noise and notice insignificant patterns if there are too many features. To train a model, not every attribute is utilized. Feature selection is crucial since correlated and non-redundant features may help us enhance our model. Furthermore, it not only helps to speed up the training process but also reduces the model's complexity and keep the simplified model, it also facilitates comprehension, and enhances its accuracy, precision, or recall metrics and generalization capability of the model. The curse of dimensionality can also be avoided if the right features are chosen for ML model training.

'Feature ranking' ranks each feature according to its relevance using a range of scoring metrics. It is critical to evaluate the model's applicability if selecting the right attributes is necessary. When building the model, only the features with the highest ranking may be considered to improve the system's accuracy. Without feature ranking, features that are not relevant can be considered, which would make the model perform worse.

3.2. Steps used in feature ranking

The steps used in the new feature selection method used in our implementation can be seen in Figure 3: i) by considering the shuffled and random features, a new set of features is produced, this new set is known as a duplicate set; ii) by considering both the original and duplicate feature sets, the model may be trained using the random forest technique; iii) information gain will be used to determine the feature relevance and will be considered when dividing the tree. This technique allows for the understanding of any feature, regardless of its importance; iv) it needs to be determined whether real features show greater importance when compared duplicate features; v) in each iteration all the above steps are repeated vi) features will be designated as important and kept if original features perform better than duplicate features; and vii) if not, the feature must be deleted and designated as irrelevant.

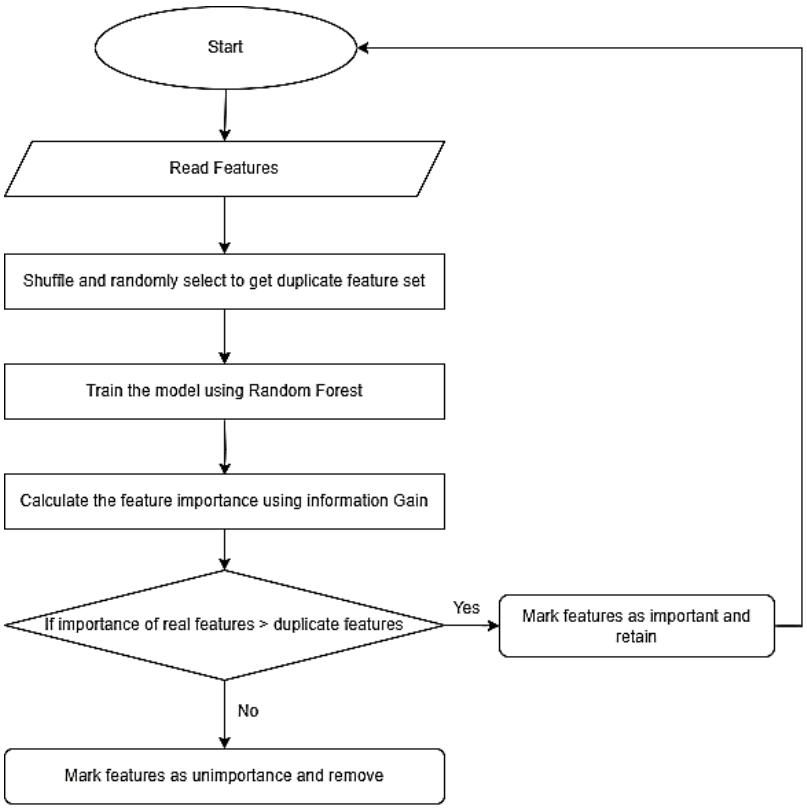

Figure 3. New feature ranking for feature selection used in our implementation

4. RESULTS

4.1. Fertilizer recommender without feature selection

Feature selection is a technique used in ML to improve accuracy. By focusing on the most important variables and removing the redundant and unimportant ones, it also improves the algorithms' ability to anticipate outcomes. Without feature ranking, the model showed the accuracy as 85% as shown below in the Figure 4. Based on the ranks, best features are selected for training.

```
accuracy_score(y_test, rf_all_features.predict(X_test))

0.8557692307692307
```

Figure 4. Accuracy before feature ranking implementation

4.2. Feature ranking given to fertilizer recommender

As illustrated in Figure 4, the accuracy of the system is 85% prior to the implementation of the feature selection approach. By quantifying the contribution of input characteristics to the overall performance of ML models, feature ranking improves accuracy. Figure 5 displays the ranks that our new technique assigned to the features. When features with ranks of 1 and below are regarded as the greatest characteristics, and features with values lesser than 1 can be disregarded, the accuracy and system efficiency will both increase.

```
selected_rf_features.sort_values(by='Ranking')
```

	Feature	Ranking
0	ph	1
13	borax	1
12	znsulphate	1
11	copper	1
10	manganeses	1
9	iron	1
7	zinc	1
8	boron	1
5	k	1
4	p	1
3	n	1
2	orgcarbon	1
1	ec	1
6	sulphur	1
14	fesulphate	2
16	mnsulphate	3
15	cusulphate	4

Figure 5. Ranks assigned to feature by our algorithm

When we use only the ranking features to create the recommendation system, the system's efficiency rises to 99% from 85%. A portion of the fertilizer recommendation findings (fertilizer suggestions made for paddy crops) are displayed in Figure 6. The R2 square for forecasting fertilizers like DAP, potassium muriate, urea, and farm yard waste is 0.99, which is the highest result that can be anticipated, and indicating that the model we have created provides extremely good accuracy.

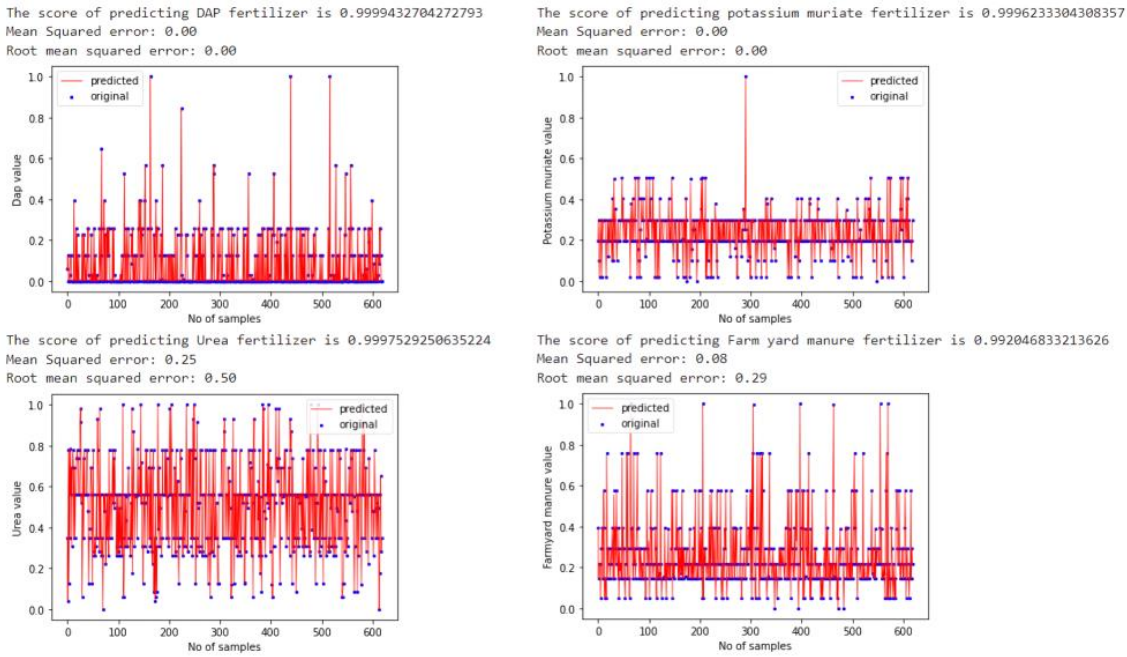

Figure 6. Fertilizer recommendation for paddy crop

5. CONCLUSION

With our fertiliser recommender, farmers may get a personalised report with all the fertilisers and their amounts, which will help them achieve better farming outcomes. It is possible to anticipate robust crop growth, larger yields, and greater farmer income if agricultural fields are fully fertilized. Maintaining the soil's health will benefit from extensive fertilization. The fertilizer recommender is implemented using an ensemble technique called the bootstrap aggregate approach. When feature ranking is used and just the ranked characteristics are employed, as this paper discusses, we can observe an increase in efficiency from 85% to 99% for the fertilizer recommender.

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