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"Smart Farming in the Indian Context: Fertilizer Prediction through Ensemble Machine Learning Based Soil Nutrient Analysis"

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Abstract:

The agricultural landscape in India is undergoing a transformative shift with the integration of advanced technologies to enhance productivity and sustainability. Recognizing the critical role of soil health in agricultural outcomes, this research leverages advanced algorithms to analyze and interpret soil nutrient data, providing farmers with accurate and timely recommendations for optimal fertilizer application. The methodology involves the collection of comprehensive soil nutrient information from various regions, utilizing state-of-the-art sensing technologies. Relationships between soil nutrient levels and crop performance are established through the applying ML models, which include regression & classification methods. The purpose of this study is to create a fertilizer prediction model capable of anticipating fertilizer requirements based on specific soil characteristics, crop types, and regional variations. The anticipated benefits of this research include improved resource utilization, enhanced crop yields, and reduced environmental impact through the targeted application of fertilizers. By providing farmers with precise recommendations tailored to their specific soil conditions, this approach seeks to contribute to sustainable agricultural practices, economic efficiency, and overall food security in the Indian context. This paper underscores the potential of machine learning applications in revolutionizing traditional farming practices by introducing data-driven decision-making processes.

Keywords: fertilizer recommendation, soil nutrients, machine learning, ensemble technique.

1. Introduction

Agriculture stands as a cornerstone of India's economic and social fabric, providing livelihoods to a substantial portion of its population and contributing significantly to the nation's GDP [3] In the pursuit of ensuring food security for a burgeoning population, the agricultural sector faces multifaceted challenges, including resource optimization, environmental sustainability, and the need for increased productivity. One pivotal aspect of this challenge is the judicious management of fertilizers, which play a vital role in enhancing crop yield but, if mismanaged, can lead to environmental degradation and economic inefficiency.[2] This research paper focuses on a transformative approach to address the intricacies of fertilizer management in Indian agriculture — Precision Fertilizer Prediction through

Machine Learning.[5,6] In an era marked by rapid technological advancements, machine learning emerges as a powerful tool capable of revolutionizing traditional agricultural practices. The integration of machine learning techniques aims to empower farmers with predictive insights, enabling them to make informed decisions about fertilizer application, optimizing resource utilization and minimizing environmental impact.[4]

The significance of precision agriculture in India cannot be overstated, particularly in the context of smallholder farmers who form the backbone of the agricultural landscape.[3] Traditional methods of fertilizer application often lack precision, leading to suboptimal use of resources and potentially contributing to soil degradation. This research endeavors to explore the potential of machine learning models in predicting optimal fertilizer requirements, tailoring recommendations to the specific needs of diverse crops and soil types prevalent in the Indian subcontinent.[6]

In this research paper precision fertilizer prediction will navigate through the ensemble machine learning model, examining their adaptability to the complexities of Indian agriculture. The objective is to shed light on the feasibility, accuracy, and scalability of machine learning applications in predicting fertilizer needs, considering the vast and varied agro ecological zones present in the country.[13]

The structure of this paper unfolds in a manner that guides the reader through the evolution of precision agriculture, the challenges associated with traditional fertilizer management, and the potential benefits that ensemble machine learning can bring to this domain. We will delve into case studies, methodologies, and empirical findings from existing research to provide a comprehensive understanding of the current landscape and identify areas for further exploration.

The transformative potential of precision fertilizer prediction through ensemble machine learning extends beyond individual farm productivity; it holds the key to sustainable and resilient agricultural practices, aligning with national objectives for environmental conservation and inclusive growth.[11] This research paper strives to contribute to the ongoing discourse on leveraging technology to enhance agricultural practices, offering insights that can inform policymakers, researchers, and practitioners alike on the journey towards a more efficient and sustainable future for Indian agriculture. The summary of contributions in this work are:

1. Along with public dataset, this work contributes by evaluating the method with self-data preparation. This is achieved with the development of soil content sensor module.
2. Development of ensemble approach for target fertilizer recommendation class.
3. Evaluation of the proposed system on public and self-dataset with proper validation steps.

The main aim of this research paper is to developed the ensemble model and compare with to other machine learning models like SVM, RF, KNN etc. [12]

This research paper planned as: section2 reviews of the traditional fertilizer forecasting paradigm are described. Section 3 the optimized ensemble model for fertilizer prediction is specified. In this research paper section 4 we show the result and analysis work and finally we conclude the research at section 5.

2. Related Work:

In 2023, Olusegun Folorunso et al. [1] stated that a systematic review of the use of machine learning models for soil nutrient properties prediction in agriculture. The studies were evaluated based on six quality criteria, and the majority of them failed to meet at least one of the criteria. The paper discusses the importance of soil quality for sustainable food production and highlights the use of soil quality indicators (SQI) to quantify soil framework. The authors also examine the use of digital soil mapping (DSM) and intelligent soil management systems in agriculture. Overall, this paper provides valuable insights into the use of machine learning in agriculture and highlights the importance of soil quality for sustainable food production

In 2023, Priti Jorvekar et al. [2] this paper includes a literature review of related works in the field of crop yield prediction. The review covers various techniques and algorithms used for predicting crop yields, such as linear regression analysis, ZT crop management technique, and machine learning algorithms. The review also highlights the drawbacks of conventional methods and the need for new prediction approaches using deep learning models.

In 2019, S.Bhanumathi, M.Vineeth and N.Rohit [4] stated that importance of crop yield prediction in agriculture and how data mining techniques can be used to create a precise and accurate model for predicting crop yield. The authors highlight the key attributes that are analyzed to predict crop yield, including location, soil composition, and weather conditions. They also discuss the use of machine learning algorithms like artificial neural networks and random forest to create a model for crop yield prediction. The paper emphasizes the importance of precision agriculture in optimizing production and soil health and providing recommendations to farmers based on the predicted crop yield and atmospheric/soil parameters of their land. Overall, the paper provides valuable insights into the use of data mining techniques for crop yield prediction and their potential impact on agriculture.

In 2022, Amilia Nongbet et al. [5] the authors discuss the innovative use of nanotechnology in material design and consumer product development, particularly in the creation of custom nanofertilizers. The study emphasizes the transformative potential of nanofertilizers in addressing challenges related to traditional manure application, including minimizing fertilizer expenses, reducing emission hazards, and enhancing crop productivity through targeted distribution and controlled release of nutrients. The authors also underscore the role of nanofertilizers in boosting crop growth and production while serving as carriers for macro- and micronutrients. It has been shown that the effects of nanofertilizers differ depending on the kind of plant and are impacted by the size, shape, concentration, and mode of administration of the nanoparticles. In addressing the need for smart and sustainable agricultural methods, the research highlights how crop output can be increased and soil fertility can be strengthened by applying nanofertilizers. The advantages of nanofertilizers over traditional chemical fertilizers are also covered, along with the synthesis and mechanistic explanation of how they improve soil fertility.

In 2019, Yao Luo et al. [6] According to, the Guizhou plateau has relatively little soil erosion because carbonate rocks underlie it, and thin soil and a watershed are the main causes of the land degradation issue. By adjusting the amount of irrigation water used, the tillage techniques, and the amount of fertilizer applied, grain productivity was very low. Despite this, limited research has been conducted on fertigation using learning techniques, highlighting a gap in the exploration of precision agriculture methods. Accurately predicting the right fertilizer based on soil parameters remains a significant challenge. To address this, there is a critical need to develop a machine learning-based fertilizer prediction model that can enhance accuracy in recommending optimal fertilization strategies. In order to close this gap, this study focuses on applying machine learning algorithms to anticipate the most suitable fertilizers based on comprehensive soil parameters. Additionally, the research explores various fertigation techniques, providing a range of choices to further investigate and understand the intricate relationship between soil conditions and crop nutrient requirements. This initiative not only addresses the immediate need for accurate fertilization but also contributes to advancing precision agriculture practices for sustainable and efficient crop cultivation.

Chawla et al. [7] applied fuzzy logic to statistical time series models for crop yield prediction. Author's predictive factors included rainfall and temperature, classifying the results into two distinct levels.

Armstrong et al. [8] a study using ANN to estimate rice yield in the districts of Maharashtra, India. They examined temperature, precipitation, and the evapotranspiration of a reference crop within a given range as part of their research. From 1998 to 2002, the researchers gathered historical records from the Indian Government archive.

Petkar et al. [9] collaborated with the previously mentioned authors (Armstrong et al.) in researching rice crop yield prediction. They applied SVM and NN to establish a novel decision system. This system functioned as an interactive interface that allowed users to enter pertinent data and receive outputs relating to the forecast of rice crop yield.

Chakrabarty et al. [10] the examination of crop prediction in Bangladesh, a nation known for growing three main crops, mainly three types of rice. They used a deep neural network in their study, taking about 46 parameters into account. These characteristics included the texture, consistency, structure, type of fertilizer applied, and reactivity of the soil. The purpose of the study was to use these parameters to forecast and assess crop outcomes.

Mnjula et al. [11] delved into the development of a robust a model for crop selection and yield prediction that takes into consideration a variety of indicators, including temperature, vegetation, and normalized difference vegetation. Their approach distinguished between agronomic, climatic, and other disruptions that could affect prediction outcomes, going beyond the conventional considerations. The purpose of this subtle separation was to offer a better comprehension of the fundamental elements affecting crop selection as well as yield estimation. The integration of these various factors into their model marked a significant step toward a more holistic and accurate approach to crop prediction.

Verma et al. [12] chose a different approach, using soil datasets to predict crops using classification algorithms, namely Naïve Bayes and K Nearest Neighbor (KNN). Important soil nutrient data, such as pH level, iron, sulfur, phosphorus, potassium, nitrogen, zinc, copper, manganese, and organic carbon, were covered by the databases. The researchers sought to anticipate and categorize appropriate crops based on the unique properties of the soil by applying these classification approaches and taking into account a variety of soil components. This approach not only contributes to accurate crop prediction but also facilitates informed decision-making for farmers by suggesting crops best suited for their soil conditions. In their investigation into corn yield prediction, Kalbande et al. [13] used the SVR, MPR, and RFR models. The researchers conducted a thorough evaluation of these models, employing various performance error metrics such as MAE, RMSE, R2squared values. The objective was to meticulously assess the performance of each regression model and analyze its accuracy and predictive capabilities in estimating corn yield. By employing a diverse set of error metrics. This research contributes to the ongoing exploration of accurate and reliable methods for predicting corn yield, ultimately supporting advancements in agricultural decision-making and enhancing productivity in corn cultivation.

Ananthara et al. [14] The CR algorithm was developed by using beehive clustering techniques to forecast agricultural productivity. Important elements including crop sensitivity, soil type, pH, humidity, and crop type were taken into account in the author's methodology. When the algorithm was evaluated against the CR algorithm on yields of rice, sugarcane, and paddy in India, it showed an accuracy of 85%.

Awan et al. [15] created a complex framework using clustering kernel techniques to estimate farm yield. The plantation, latitude, temperature, and rainfall precipitation within that latitude were all taken into account in the author's model. The weighted k-means kernel technique with spatial limitations was utilized by the researchers, who specifically examined its suitability for oil field applications.

3. Proposed work

In smart agricultural system, fertilizer supply to the soil with respect to the actual needs is important factor. Under supply leads to the low crop production outcome and over supply also results in death of some crops along with over economic losses.

The primary goal of the research described in this article is to design a fertilizer recommendation system based on soil nutrient content. The nutrient content estimation in current scenarios is time consuming and lab dependent process. Thus the work presented in this article contributes in terms of soil testing sensor module for data collection and a model for prediction of fertilizer required based on the data collected. Figure 1 shows the structure of the end-to-end system model.

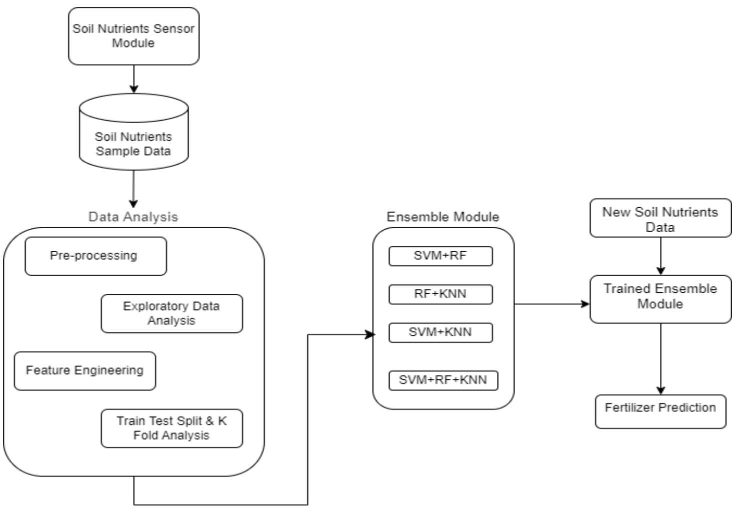


Figure 1: Proposed end to end system Framework

3.1 Data set preparation

3.1.1 Preparation based on Standard Public Datasets

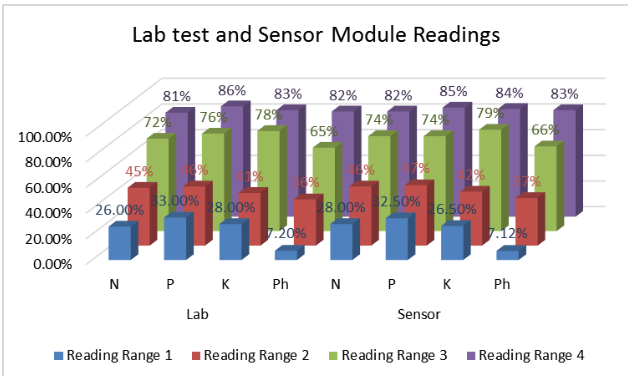
Pre-processing is first carried out using the data. Using preprocessing we clean the raw data, find the missing values, outliers and remove that missing values and outliers using different statistical techniques. Pre-processing includes the step of data normalization. The functional cleaning of data is known as data normalization. It is therefore helpful for keeping many forecasts accurate and adjusting data to match our expectations. Better normalization outcomes are obtained by scaling data inside a specific range, such as [0, 1]. One technique for normalizing data is the Z-score normalization. In this case, the mean (S) and standard deviation (σ) of the data S are used to normalize the data.

3.1.2 Self-Dataset Preparation

Sensor based system for collecting parametric data is developed. The system consist of cost effective sensors that are sensitive to respective soil contents. The sensor range is tested with varying range of concentration of specific soil contents such as nitrogen, potassium and phosphorus. The ratio of these soil nutrients is varied by first collecting soil the soil from the farm field. The soil is then tested in soil testing lab for specific information of the nutrient levels. The nutrient levels obtained from soil is then verified with use of developed sensor based system. After this step, the soil is added with 15-0-0 fertilizer with 1:10 ratio. In this ten parts of the soil is mixed with 1 part of the fertilizer. Similarly, this mixing ratio is varied up to 4:10 i.e. 2:5 ratio. In which 10 parts of the soil is mixed with 4 parts of the fertilizer. This mixing is done by considering weighing based approach and not as volumetric approach. The fertilizers that are available in market are based on weighing scale in kilograms thus, mixing unit followed is also kilograms.

Along with this other nutrient ratios are also considered with 0-15-0 and 0-0-15 pattern. The mixing of these patterns are also carried out similar to first pattern of fertilizer. This way total 1200 samples are prepared.

All the samples with different mixing rations are then checked with soil testing lab and the sensor module is also used that is designed for data collection. This way sensor module sensitivity to specific soil nutrient content is first cross verified with that of soil testing lab reports.



Graph1. Analysis of Lab Test and Sensor Module Readings

Graph1 shows the change the error pattern obtained by comparison of the lab reports and sensor module outcomes. Based on average analysis and error patterns, it is found that the soil nutrient sensor module shows fixed results for all the experimentation scenarios.

3.2Feature extraction

For the proposed approach ensemble classification methods, it is important to have unique relevant features of the data with respect to specific class. The maximum, minimum, standard deviation and kurtosis are estimated as additional features for each row of data vector. This feature vector is then used for training of the neural network model.

N	P	K	Ph	Target
245	9.9	144	7.46	15-15-0
273	7.5	138	7.62	10-26-26
280	12.9	144	7.59	17-17-17
220	6.6	201	7.64	0-20-20
340	11.2	182	7.63	DAP
257	11.4	238	7.43	UREA
276	6.8	270	7.62	28-28
270	8.1	213	7.63	14-35-14
295	14.3	245	7.58	12-32-16
232	5.3	282	7.55	15-30-15

Table 1: Data samples from dataset

3.3Learning approach: (Ensemble)

SVM is a supervised machine learning technique that may be applied to regression and classification problems. The process involves identifying the hyperplane that divides the data into the most distinct classes. The distance between the hyperplane and the closest data points from each class is called the margin, and the goal of SVM is to maximize it. An ensemble learning technique called Random Forest constructs several decision trees and combines their forecasts. It is applicable to jobs involving both regression and classification. A random subset of the characteristics and a random subset of the data are used to construct each tree in the forest. KNN is an easy-to-understand technique that may be applied to regression and classification problems. A new data point is classified according to the majority class of its k-nearest neighbours. KNN is an instance-based, non-parametric algorithm.

The choice between SVM, KNN, and RF depends on the specific characteristics of the data, the problem at hand, and computational considerations. SVM is powerful in high-dimensional spaces, KNN is simple and adaptable, while Random Forests often provide high accuracy and handle complex datasets well. The permutations and combinations of Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (KNN), we are essentially considering different ways of combining these algorithms in the context of an ensemble.

SVM- The SVM algorithm finds a hyperplane that best divides a dataset into classes. The goal is to maximize the margin between the data points of the different classes. Following equations depicts objective function and objective function with slack variables.

$$\text{Objective Function: } \min_{w,b} \frac{1}{2} ||w||^2$$

$$\text{Subject to : } y_i(w.x_i + b) \geq 1, \forall i$$

For the soft margin SVM, we introduce slack variables ξi to allow some misclassifications:

Objective function with slack variables: $\min_{w,b,\xi} \frac{1}{2}||w||^2 + C\sum_{i=1}^{n} \xi i$

$$\text{Subject to } y_i(w.x_i + b) \geq 1 - \xi i, \ \forall i$$

$$\xi i \geq 0, \forall i$$

KNN- The k-NN algorithm classifies a data point based on the majority class among its k nearest neighbors. Following formula shows the distance metric (Euclidean distance):

$$d(x, x_i) = \sqrt{\sum_{j=1}^{m} (x_j - x_{ij})^2}$$

RF- The Random Forest algorithm is an ensemble method that uses multiple decision trees to make a classification or regression decision. Following equation shows the Decision tree construction for each tree in the forest:

$$Split\ criterion: \max_{\theta} [Information\ Gain\ (\theta)]$$

$$Information\ Gain\ (D, \theta) = H(D) - \sum_{i=1}^{k} \frac{|D_i|}{|D|} H(D_i)$$

Dynamically select the algorithm (SVM, RF, or KNN) for each instance based on its characteristics or the performance of the models on similar instances. Allows the ensemble to adapt to different patterns in the data, potentially improving overall performance.

The effectiveness of the ensemble often depends on the diversity of the base models. Combining models with different underlying principles or strengths enhances diversity. Consider the computational cost of training and deploying different combinations such as SVM+RF, RF+KNN and KNN+SVM. The ensembles may be more computationally intensive than others. Proper validation and hyperparameter tuning are crucial to ensuring the ensemble performs well on unseen data. The choice of permutation or combination depends on the specific characteristics of the problem, the nature of the data, and computational constraints. Experimentation and thorough validation are essential in determining the most effective ensemble strategy for a given task.

4. Result and Analysis

4.1 Train-Test split & K-fold analysis

The train-test split is a fundamental technique in machine learning for evaluating the performance of a model. The machine learning model is trained using the training set. Typically, it constitutes a larger portion of the dataset (e.g., 70-80%). The test set is utilized to assess how well the model performs with unknown data. A smaller portion of the dataset is reserved for testing (e.g., 20-30%).

A resampling method called K-Fold Cross-Validation is used in machine learning to evaluate a model's performance and capacity for generalization. The main idea is to divide the dataset into K folds of equal size. Then, the model is trained and tested K times, with each iteration utilizing a different fold as the test set. K-Fold Cross-Validation is a resampling procedure used to evaluate the performance of a model on a limited data sample. The data set is split into K smaller sets (folds). The model is trained on $K-1$of these folds and tested on the remaining fold. This process is repeated K times, with each of the K folds used exactly once as the test data. The final performance metric is the average of the performance metrics from each fold. Following equation depicted K-fold cross-validation:

$$M = \frac{1}{K}\sum_{k=1}^{K} M_k$$

Where, K is the “number of folds”.

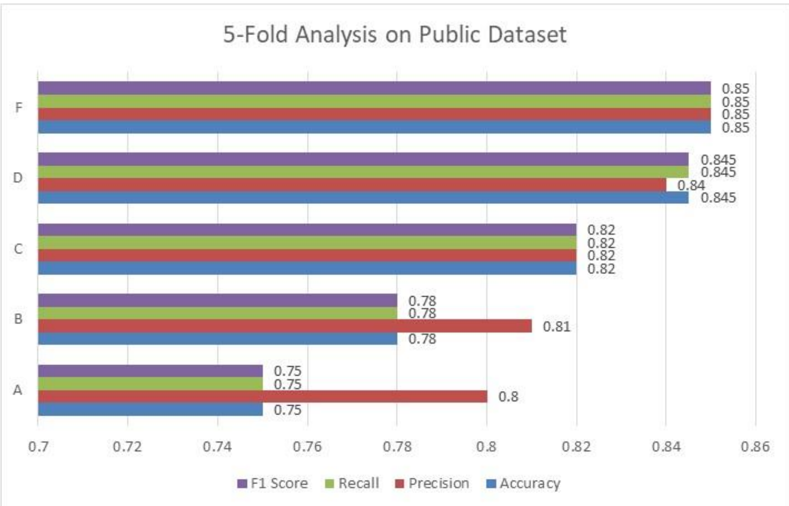
M_k is the “performance metric” (e.g., accuracy, loss) for the kth fold.

M is the “mean performance metric across all folds”.

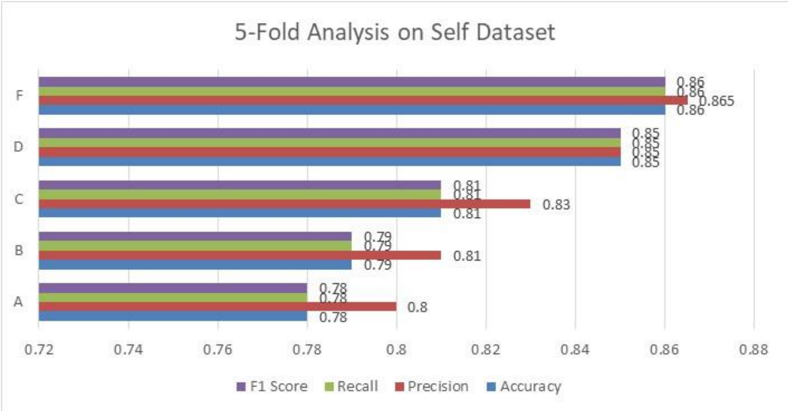
Then, to produce a more reliable estimate of the model's performance, the performance metrics are averaged over these iterations. When considering a model's performance, K-Fold Cross-Validation offers a more thorough evaluation than a straightforward train-test split. It is a valuable tool for understanding how well a model generalizes to distinct subsets of information and is widely used in both model evaluation and hyperparameter tuning.

Fold	Train Part	Test Part	Train Folds	Test Fold
1	1000	300	1,2,3,4	5
2	1000	300	1,2,3,5	4
3	1000	300	1,2,4,5	3
4	1000	300	1,3,4,5	2
5	1000	300	2,3,4,5	1

Table 2 Sample size details of train, validation and test split



Graph2. Public Dataset 5-Fold Analysis

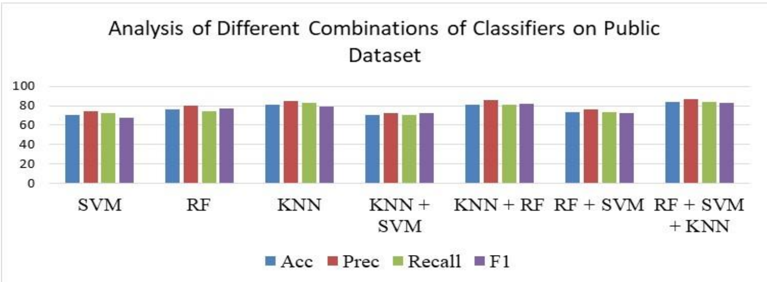


Graph3. Self Dataset 5-Fold Analysis

Accuracy	TP+TN/(TP+TN+FP+FN)
Specificity	TN/(TN+FP)
Sensitivity	TP/(TP+FN)
Precision	TP/(TP+FP)
Recall	TP/(TP+FN)
F1 Score	2*(Recall*Precision)/(Recall+Precision)

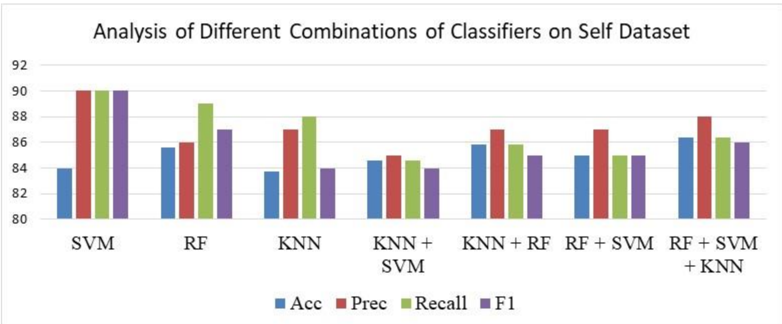
Table 3 Performance Evaluation. Formulae

In this graph 4 shows that all machine learning and ensemble models (SVM, RF, KNN, KNN+SVM, KNN+RF, SVM+RF and RF+SVM+KNN) accuracy, precision, recall and f1 score on public dataset.



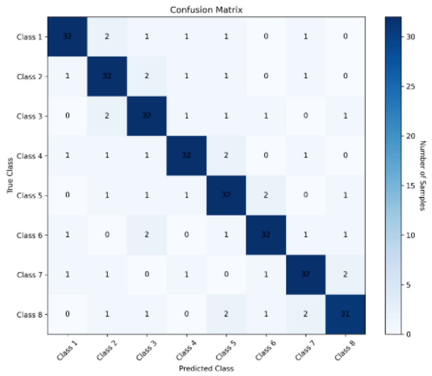
Graph4. Model Analysis on Public dataset

Graph 5 shows that all machine learning and ensemble models (SVM, RF, KNN, KNN+SVM, KNN+RF, SVM+RF and RF+SVM+KNN) accuracy, precision, recall and f1-score on self dataset.

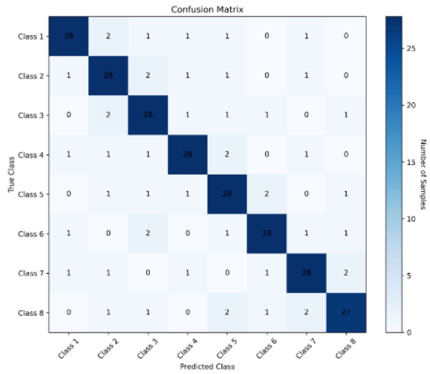


Graph5. Model Analysis on Self dataset

Confusion Matrix with respect to test sample size in each public and private dataset.



Graph 6. Public Dataset Confusion Matrix Analysis



Graph 7. Self Dataset Confusion Matrix Analysis

In this scenario, the confusion matrix reflects the performance of an 8-class classification model with an accuracy of 85%. The Off-diagonal elements show misclassifications, whereas diagonal elements show the quantity of samples that were correctly classified. Every column represents the anticipated class, while every row represents the actual class. The model shows relatively balanced performance across classes, with varying degrees of correct and incorrect predictions. A comprehensive evaluation reveals insights into the model's strengths and weaknesses in distinguishing between different classes.

In this context, the confusion matrix represents the outcomes of an 8-class classification model with an improved accuracy of 87%. The matrix vividly illustrates the distribution of correct and incorrect classifications across different classes. Notably, the Off-diagonal elements show misclassifications, whereas diagonal elements show the quantity of samples that were correctly classified. The model exhibits enhanced overall performance, resulting in fewer errors and a higher proportion of correct predictions. This higher accuracy is reflected in the improved precision and reliability of the model in classifying samples within the diverse set of eight classes.

Achievements of the Proposed RF+KNN+SVM Ensemble Model:

1. Enhanced Predictive Performance: The ensemble of Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) models capitalizes on the strengths of each individual algorithm, resulting in improved predictive accuracy. The combination of diverse learning strategies contributes to a more robust and reliable prediction model.
2. Reduction of Overfitting: The ensemble approach helps mitigate overfitting, a common issue in machine learning models. By leveraging the diversity of RF, KNN, and SVM, the ensemble model achieves better generalization to unseen data, enhancing its performance in real-world scenarios.
3. Comprehensive Learning: Each constituent algorithm in the ensemble model specializes in different aspects of the data, allowing for a more comprehensive understanding of complex patterns. This collective intelligence contributes to a more nuanced and accurate prediction, particularly in scenarios where individual models might struggle.

4. Improved Robustness: The combination of RF, KNN, and SVM provides a balanced trade-off between model complexity and simplicity. This results in an ensemble model that is more robust to variations in the dataset, making it suitable for diverse applications and datasets.

5. Conclusion

In conclusion, this study highlights the transformative impact of integrating advanced machine learning technologies into Indian agriculture, specifically focusing on optimizing fertilizer application based on soil nutrient analysis. By leveraging sophisticated algorithms and sensing technologies, the research aims to develop a predictive model that offers farmers precise recommendations tailored to their unique soil conditions. The anticipated benefits include improved resource utilization, increased crop yields, and minimized environmental impact. Overall, this approach signals a shift towards data-driven decision-making in farming, contributing to sustainable practices, economic efficiency, and bolstering food security in India. The study underscores the potential of machine learning to revolutionize traditional agricultural practices and empower farmers with valuable insights for a more resilient and productive sector.

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