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Article

Intelligent Crop Recommendation Framework Using Hybrid Learning with Macro and Micronutrients.

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Abstract:
Purpose:
Selecting suitable crops according to soil and environmental conditions remains a major challenge in agriculture. Conventional crop selection practices often depend on experience-based decisions and may not effectively consider variations in soil nutrients and climatic conditions, leading to inefficient resource utilization and reduced productivity. It aims to develop a data-driven framework for improving agricultural decision-making.
Study approach:
A framework is developed using supervised ensemble machine learning techniques. The proposed approach integrates soil macro-nutrients & micronutrients, soil properties, and climatic parameters for crop suitability prediction. Multiple machine learning methods, including Random Forest, XGBoost, Logistic Regression, and LightGBM, were evaluated. A hybrid stacking ensemble framework was developed by combining multiple base learners with Logistic Regression as a meta-learner. framework performance was assessed using independent testing and stratified 5-fold cross-validation.
Findings:
Proposed hybrid stacking framework achieved the highest performance with 96.70% testing accuracy, outperforming individual models. Random Forest, XGBoost, Logistic Regression, LightGBM and Hybrid algo achieved accuracies of 71.70%, 90.15%, 94.35%, 94.55% with highest 96.70% [Hybrid stacking], respectively. The results demonstrate improved prediction capability through ensemble integration.
Limitations:
The framework requires further validation using real-world field datasets from diverse geographical regions. Future work can incorporate real-time sensor data for adaptive recommendations.
Practical and social implications:
The framework can support farmers and agricultural stakeholders by providing data-driven crop recommendations, promoting efficient resource utilization and sustainable farming practices.
Originality:
This study presents a nutrient-aware hybrid ensemble framework integrating macro-micronutrients and environmental parameters for intelligent crop recommendation, providing a foundation for smart agricultural decision-support systems.
Keywords: Crop recommendation system, supervised machine learning, Macro and Micronutrients, Crop Prediction, Machine Learning.

1. Introduction

Agriculture plays a vital role in global food security and economic development; however, increasing population demands, climate variability, soil degradation, and inefficient resource utilization have created significant challenges for sustainable crop production. Selecting a suitable crop according to soil and environmental conditions is a complex decision-making process that directly affects productivity and profitability. Traditionally, farmers rely on personal experience, conventional practices, and static agricultural recommendations, which may not effectively address dynamic variations in soil characteristics and climatic conditions. Therefore, intelligent and data-driven crop recommendation systems have gained importance for improving agricultural decision-making.

Machine learning (ML) techniques have emerged as effective tools in modern agriculture due to their capability to identify hidden patterns from complex agricultural datasets. ML-based approaches have been widely applied in crop recommendation, crop yield prediction, disease identification, and precision farming applications. Several supervised learning algorithms, including decision trees, artificial neural networks, support vector machines, and ensemble models, have been investigated to recommend suitable crops based on soil and environmental attributes [1], [6], [15]. These approaches provide a scientific alternative to traditional farming practices by enabling data-driven crop selection and improved resource management.

Various researchers have developed ML-based crop recommendation frameworks using soil and climatic parameters. Doshi et al. proposed an intelligent crop recommendation system using machine learning algorithms to assist farmers in selecting appropriate crops based on agricultural conditions [15]. Similarly, neural network-based approaches have been explored to capture complex relationships between agricultural parameters and crop suitability [6]. Other studies have demonstrated the applicability of supervised learning models for crop recommendation by utilizing soil properties and environmental conditions [2], [18], [31]. Although these approaches have shown promising results, many existing systems are limited by restricted feature selection and dependency on conventional soil parameters.

Ensemble learning techniques have gained significant attention due to their ability to combine multiple learning algorithms and improve prediction robustness. Ensemble-based crop recommendation approaches have demonstrated improved performance by reducing individual model limitations and enhancing generalization capability. Kulkarni et al. introduced an ensemble-based crop recommendation approach to improve crop productivity [24]. Similarly, recent studies have explored ensemble machine learning frameworks for effective crop cultivation recommendation and sustainable agricultural decision support [19], [22]. However, existing ensemble approaches often focus on limited agricultural parameters and require further exploration of diverse nutrient and environmental factors.

Most conventional crop recommendation systems primarily consider macronutrients such as nitrogen (N), phosphorus (P), and potassium (K), along with soil pH, temperature, and rainfall. These parameters are essential for plant growth; however, micronutrients such as zinc, iron, copper, manganese, and boron also play significant roles in plant physiological processes, enzyme activation, and crop quality. Deficiency of micronutrients can negatively influence crop development even when macronutrient levels are sufficient. Therefore, integrating both macro- and micronutrient characteristics can provide a more comprehensive representation of soil health and crop requirements [7], [9].

Recent advancements in agricultural intelligence have also explored hybrid learning models, explainable artificial intelligence, and IoT-enabled farming systems. Deep learning and hybrid approaches have demonstrated strong capabilities in modelling complex agricultural relationships; however, challenges related to computational requirements, interpretability, and practical deployment remain significant [10], [30]. Additionally, IoT-based agricultural systems enable real-time monitoring of soil and environmental conditions, supporting adaptive decision-making for smart farming applications [3].

Despite significant progress, existing crop recommendation systems still face several challenges, including limited parameter diversity, insufficient validation strategies, lack of model interpretability, and limited generalization across different agricultural conditions. Review studies have highlighted the need for robust machine learning frameworks capable of integrating heterogeneous agricultural data and providing reliable recommendations [12], [21]. Furthermore, many existing studies evaluate models using limited experimental settings without extensive validation, which may affect the reliability of prediction outcomes.

To address these limitations, this research proposes an intelligent crop recommendation framework using hybrid ensemble machine learning by integrating soil macro-nutrients, micronutrients, and environmental parameters. The proposed framework evaluates multiple supervised learning models and develops a hybrid stacking approach to improve prediction accuracy and reliability. The research aims to provide an effective decision-support system for sustainable agriculture by enabling data-driven crop selection and optimized resource utilization.

In conclusion, from the literature review, it is evident that although great strides have been achieved in developing crop recommendation framework through machine learning, there is still room for improvement by developing a complete approach that considers not only nutrient levels but also other environmental factors.

After Review related study and survey, the researcher identifies that a farmer friendly framework is still required that cover both macro and micronutrients of soil with basic environmental factors. To address these limitations, this paper proposes workflow of a data-driven crop recommendation framework indicates in figure 1, that incorporates environment factor and soil pH along with macro and micronutrient parameters using a hybrid ensemble machine learning approach. Balanced crop-wise datasets and systematic preprocessing techniques are employed to improve the reliability and predictive accuracy of the framework.

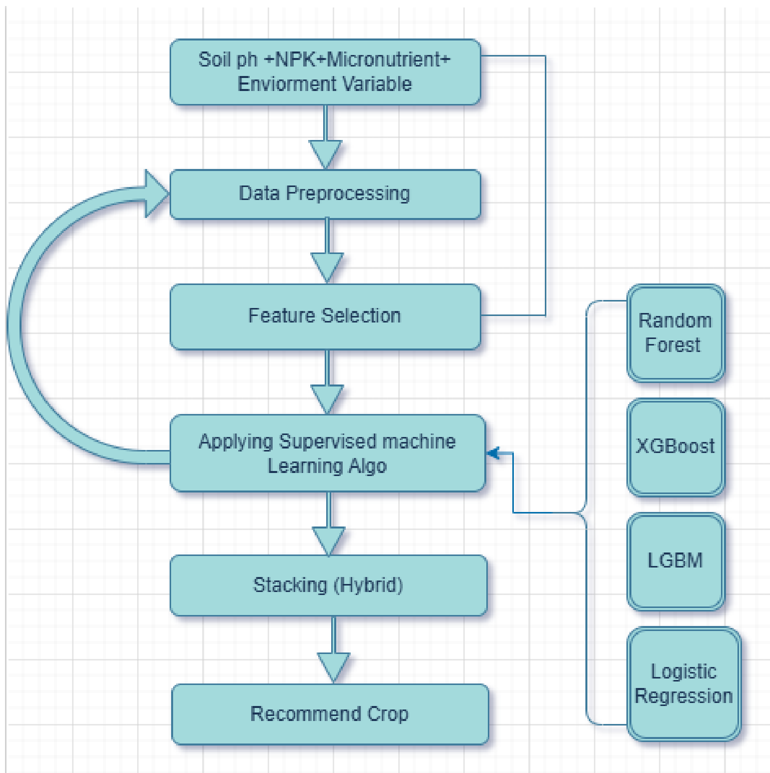

Figure 1: - Proposed Framework for crop recommendation system

The suggested model incorporates different supervised algorithms such as Random Forest, Logistic Regression, XGBoost, and LGBM in a hybrid stacking framework. This allows for a combination of learning from individual models with strengths in balance. Using soil properties, nutrient presence indices, and agriculture-related attributes, the system will provide reliable crop recommendations that can be applied in various geographical locations.

The primary objectives of this work are:

1. Introducing of a generalized ensemble-based crop recommendation framework with covering the macro and micronutrients of soil along with environment and soil ph factor.

2. Comparative evaluation of multiple supervised learning algorithms and their stacked integration, and Enhancement of farmer decision-making.

By aligning machine learning methodologies with practical agricultural decision-making needs, this research seeks to bridge the gap between computational intelligence and real-world farming through the application of machine learning techniques that fit into the requirements of farming decision making.

2. MATERIALS AND METHODS

Dataset Source Description

The dataset used in this study was developed by integrating agronomic knowledge obtained from multiple secondary sources, including Soil Health Card records, ICAR recommendations, soil testing laboratory reports, agricultural guidelines, and published research literature. These sources were utilized to identify realistic ranges and suitable combinations of soil nutrient and environmental parameters associated with crop cultivation.

The size of the dataset is 5000 and it consists of thirteen input attributes, including three macronutrients (Nitrogen (N), Phosphorus (P), and Potassium (K)), five micronutrients (Zinc (Zn), Boron (B), Iron (Fe), Magnesium (Mg), and Copper (Cu)) with four Climate parameter such as Soil pH, Temperature (°C), Rainfall (mm), and Humidity (%). And the last parameter target variable represents the recommended crop. These parameters were selected because crop suitability depends on nutrient availability, soil condition, and climatic requirements. This study focuses only on five major crops: Cotton, Groundnut, Maize, Rice, and Wheat.

Parameter	Reference Source
N, P, K	Soil Health Card, ICAR Guidelines
Zn, B, Fe, Mg, Cu	Soil Testing Laboratory Reports, ICAR
Soil pH	Soil Health Card
Temperature	IMD / Meteorological Records
Rainfall	IMD / Agricultural Climate Data
Humidity	IMD / Meteorological Records

Table 1: - Reference sources used for defining soil nutrient and environmental parameter ranges for crop recommendation.

The values for each parameter were compiled and validated using information available from agricultural and soil fertility sources to ensure consistency with commonly accepted crop growth requirements. Prior to this framework development, the dataset was pre-processed through data cleaning, consistency checking, and normalization.

The selected attributes represent key soil fertility and environmental factors that significantly influence crop suitability and productivity, thereby supporting the development and evaluation of the proposed crop recommendation framework.

The Figure 2 ensures balancing of a framework, an equal number of data samples were collected for each crop. Specifically, 1,000 records were used per crop, which helped to reduce class imbalance and improved the fairness of training the machine. And Table 2 shows the list of the parameter used for the research and their importance in the research.

Figure 2: Class Distribution for each crop.

Parameter	Category	Importance in Crop Growth
Nitrogen (N)	Macronutrient	Require for chlorophyll formation, protein synthesis, and plant growth
Phosphorus (P)	Macronutrient	Supports root development, energy transfer (ATP), and flowering processes
Potassium (K)	Macronutrient	Regulates enzyme activation, water balance, and improves disease resistance
Zinc (Zn)	Micronutrient	Important for enzyme activity and plant hormone regulation
Iron (Fe)	Micronutrient	Essential for chlorophyll synthesis and photosynthesis
Boron (B)	Micronutrient	Supports cell wall formation, pollen development, and nutrient transport
Manganese (Mn)	Micronutrient	Plays a role in photosynthesis and nitrogen metabolism
Copper (Cu)	Micronutrient	Involved in enzyme systems and plant metabolic processes
Soil pH	Soil Property	Check nutrient availability and microbial activity in soil.
Temperature	Environmental Factor	Influences plant metabolism, germination, and growth rate
Rainfall	Environmental Factor	Provides water required for nutrient transport and plant hydration
Humidity	Environmental Factor	Affects transpiration, plant respiration, and disease occurrence
Crop Label	Target Variable	Represents the recommended crop for the given conditions

Table 2: - Parameter included

Methods

After the dataset finalization. Different preliminary steps are implemented such as Data Processing to find out the missing and duplicate values, Statistical Analysis to find mean, variance and distribution of numerical features on nutrient concentrations , Correlation Analysis to find out pattern and trends of the dataset showing in Figure2 , Feature

Target Separation to split the dataset in feature (X) as input parameter [N, P, K, Zn, Fe, B, Mn, Cu, Soil ph, Temperature, Rainfall, Humidity] and target (Y) as output parameter [Crop Label] , Label Encoding to convert the categorical value into the numerical and apply supervised machine learning algorithm to train and test our machine. For better accuracy and result the dataset is split into 60-40 ratio. As 60 % of the dataset [800 samples] are used to train the machine and 40% of the dataset [400 samples] are used to test. Feature scaling was applied using standardization to normalize feature distribution before machine training. To avoid data leakage, preprocessing operations and machine training were performed only on the training dataset. The testing dataset remained completely unseen during training and hyperparameter selection.

For training and testing the supervised learning algorithms used such as Random Forest, XGBoost, Logistic Regression, LightGBM and Hybrid Stacking Framework.

Random Forest ensemble learning method that builds multiple decision trees and combines their outputs for accurate predictions. It handles nonlinear relationships between soil nutrients, environment and crop types effectively.

XGBoost (Extreme Gradient Boosting) is a powerful boosting algorithm that builds trees

sequentially to correct previous errors. It efficiently captures complex patterns in agricultural data like rainfall, temperature, and soil composition. This increases accuracy and speed.

Logistic Regression is a statistical classification algorithm used to predict categorical outcomes. It models the probability of selecting a particular crop based on input features. In crop recommendation, it serves as a simple and interpretable baseline model.

LightGBM is a gradient boosting framework that uses tree-based learning with faster training speed. It handles large-scale agricultural datasets efficiently with lower memory usage. This model is effective for capturing feature importance in crop recommendation tasks.

The Hybrid Stacking framework combines multiple machine learning algo to improve overall performance of the machine. It uses base algo like Random Forest, XGBoost, and LightGBM, and a meta-learner Logistic Regression to aggregate their outputs. In crop recommendation, stacking enhances accuracy by leveraging the strengths of different algorithms. The accuracy of each algorithm indicates in the table 3, that shows the stacking model achieves the highest accuracy because it combines the strengths of all individual models. By using predictions from multiple algorithms and learning how to merge them, stacking reduces individual model weaknesses and produces more reliable and accurate and suitable crop recommendation.

Algorithm	**Training Accuracy**	**Testing Accuracy**
Random Forest	72.83%	71.70%
XGBoost	90.60%	90.15%
Logistic Regression	94.70%	94.35%
LightGBM	95.43%	94.55%
Stacking	97.60%	96.70%

Table 3: Accuracy comparison of each algorithm.

Analysis

The analysis was done on the methods of supervised algorithm that reduces bias and variance while improving decision reliability. The hybrid stacking framework always performed better than any other individual classifier model, confirming the power of ensemble learning for recommending crops.

Model Validation Strategy

Stratified 5-fold cross-validation was applied to evaluate the robustness of all machine learning methods. The dataset was divided into five folds while maintaining the distribution of crop classes. Each fold was used once as validation data, and the remaining folds were used for training. The final validation performance was calculated using the average of five iterations. Below mention Table 4 shows the small difference between cross-validation and testing performance indicates that the model generalizes well to unseen samples.

3. RESULTS AND DISCUSSION

Table 4 shows the comparative analysis highlights of existing crop recommendation studies have primarily focused on conventional machine learning models using limited soil parameters, while some recent works have explored ensemble-based approaches for improving prediction performance. However, the integration of diverse agricultural attributes such as macro-nutrients, micro-nutrients, soil properties, and climatic parameters remains limited. The proposed hybrid stacking framework addresses these limitations by combining multiple learning algorithms with a meta-learning strategy, enabling improved prediction capability and stability. Furthermore, the utilization of stratified 5-fold cross-validation and independent testing provides stronger evidence of the reliability and generalization performance of the proposed crop recommendation system.

Study	ML Approach	Dataset / Parameters Used	Validation Strategy	Major Findings	Research Limitation
Doshi et al. (2018)	ML-based AgroConsultant system	Soil and agricultural parameters	Model evaluation based on dataset	Demonstrated feasibility of ML-based crop recommendation	Limited feature diversity and model comparison
Banavlikar et al. (2018)	Artificial Neural Network	Crop and soil parameters	Performance evaluation	ANN capable of learning agricultural patterns	Limited comparison with ensemble algorithms
Kulkarni et al. (2018)	Ensemble learning approach	Soil-based crop parameters	Model comparison	Ensemble method improved recommendation performance	Limited environmental and nutrient factors
Bondre & Mahagaonkar (2019)	ML algorithms for crop/fertilizer prediction	Soil nutrients	Classification-based evaluation	Demonstrated ML application in agricultural prediction	Focused mainly on fertilizer/yield prediction
A P et al. (2021)	Supervised ML algorithms	Soil and crop parameters	Experimental evaluation	ML models support data-driven crop selection	Limited discussion of model stability
Pande et al. (2021)	ML-based crop recommender	Agricultural dataset	Algorithm comparison	Showed potential of ML recommendation systems	Limited feature expansion
Jadhav & Bhaladhare (2022)	Survey of ML crop recommendation	Existing ML approaches	Review study	Identified challenges in current systems	No implemented hybrid framework
Hasan et al. (2023)	Ensemble ML model	Agricultural cultivation parameters	Model evaluation	Ensemble learning improved prediction robustness	Limited nutrient and climatic integration
Apat et al. (2023)	AI-based crop recommendation	Soil parameters	ML evaluation	Demonstrated AI application in agriculture	Limited explainability and validation discussion
Bouni et al. (2024)	Interpretable ML model	Soil/environment parameters	Model analysis	Highlighted importance of explainable AI	Limited hybrid model evaluation
K D K & Kumar J P (2024)	Ensemble ML for crop and fertilizer recommendation	Agricultural parameters	Performance comparison	Improved sustainable agriculture decision support	Limited focus on micronutrients
Baagdi et al. (2025)	Conceptual ML framework	Multi-source agricultural data	Conceptual validation	Proposed sustainable smart farming framework	No extensive experimental validation

Table 4: - Comparative analysis of existing crop recommendation approaches

The implementation of multiple supervised machine learning algorithms revealed that their performance varies because each algorithm learns patterns through a different machine learning method. The observed differences in training and testing accuracy indicate how effectively each model captures and generalizes the relationship between soil nutrients, environmental factors, and crop suitability. The Table 5 shows the evaluation metrics were used to assess the performance of the crop recommendation framework more effectively.

Precision

Precision tells us how many of the crops recommended by the system are correct. A precision value of 0.96 means the system gives correct crop suggestions most of the time and makes very few wrong recommendations.

Recall

Recall shows how well the system can find the most suitable crop from all possible options. A recall value of 0.967 indicates that the framework correctly identifies most of the suitable crops and rarely misses good options.

F1- Score

F1-Score combines both precision and recall into a single value. It helps us understand how balanced and reliable the framework is. An F1-score of 0.9669 shows that the system performs consistently and gives dependable results.

Accuracy

Accuracy shows how often the system predicts the correct crop overall. An accuracy of 97% means the machine learns the relationship between soil pH, macro and micro nutrients, and crop suitability very well and provides correct recommendations in most cases.

ML Methods	5-Fold CV Accuracy (Mean ± SD) (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest (RF)	70.93 ± 2.63	71.76	71.7	68.54
XGBoost	88.80 ± 1.42	90.32	90.15	89.83
LightGBM	94.47 ± 0.62	94.59	94.55	94.56
Logistic Regression (LR)	93.80 ± 0.59	94.77	94.4	94.26
Hybrid Stacking Framework	96.97 ± 0.29	96.66	96.65	96.64

Table 5: Performance Comparing Matrix using 5 – fold cross validation techniques.

Detailed performance analysis

A Confusion Matrix is a performance depth tool for machine learning. It is generally used to evaluate the performance of a classification framework by comparing actual vs predicted values. The confusion matrix demonstrates that the proposed hybrid ensemble framework achieves high class-wise prediction accuracy. Most predictions lie along the diagonal that indicating correct classification. Minor misclassifications occur between crops with similar soil and climatic requirements, which is expected in agricultural prediction systems. Confusion matrix is generated for testing dataset or 400 samples [split in 60-40 ratio]. In Figure 3 the diagonal value shows the correct prediction. Rest of the value shows the wrong prediction classification. Minor misclassifications occur between crops with similar soil and climatic requirements, which is expected in agricultural prediction systems. Confusion matrix is generated for testing dataset or 400 samples [split in 60-40 ratio]. In Figure 3 the diagonal value shows the correct prediction. Rest of the value shows the wrong prediction.

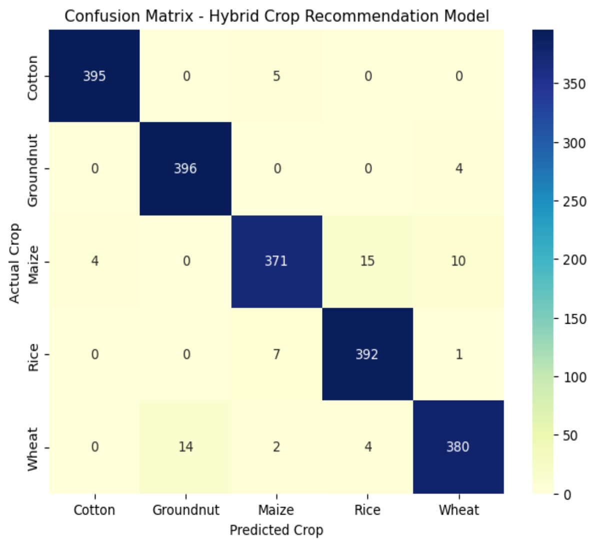

Figure 3: -Confusion matrix for the hybrid stacking Framework

Feature Importance and Analysis

The feature importance analysis was performed to understand the contribution of soil and climatic parameters towards crop recommendation.

Macronutrients Interpretation

Nitrogen

Nitrogen showed significant influence because it directly affects vegetative growth and biomass production. Crops having higher nitrogen demand show different suitability patterns compared with crops requiring lower nitrogen availability.

Phosphorus

Phosphorus contributes to root development and reproductive growth. Variation in phosphorus availability helps the framework differentiate crop nutrient requirements.

Potassium

Potassium improves stress tolerance, water regulation, and disease resistance. Therefore, potassium availability contributes to identifying crops suitable under different growth conditions.

Micronutrients Interpretation

Micronutrients such as Zn, Fe, B, Mn, and Cu were included because they influence enzymatic activity, photosynthesis, flowering, and overall crop development. Their inclusion improves the representation of soil fertility conditions beyond conventional NPK-based recommendation systems.

Environmental Interpretation

Temperature

Temperature influences germination and growth cycle. Different crops require specific thermal conditions, allowing the framework to learn climate suitability patterns.

Rainfall

Rainfall represents water availability and helps distinguish water-demanding crops from drought-tolerant crops.

Humidity

Humidity affects moisture availability and disease susceptibility, contributing to environmental suitability analysis.

Crop Suitability Pattern Analysis

The machine learning framework does not consider individual parameters independently; instead, it learns the combined relationship between soil nutrients and environmental conditions. Higher rainfall and humidity conditions influence recommendations for water-intensive crops, whereas crops adapted to lower water availability are associated with different climatic patterns.

4. CONCLUSION

This research presented a systemic and stepwise crop recommendation framework that utilizes basic climate parameter along with comprehensive macro and micronutrient profiling to improve crop suitability decisions. The important part of this study is that the researcher includes both macro and micronutrients as there are many few study that include on both nutrients for the recommend the crop as the micronutrients is also very much important for crop growth. To fulfil this gap many supervised machine learning algorithms like Random Forest, XGBoost, Logistic Regression, LightGBM are used but they give comparatively low accuracy. So, this study incorporating multiple supervised machine learning framework as a hybrid stacking approach with (96.70% accuracy), the proposed system effectively captures complex relationships between soil fertility parameters and crop requirements. The experimental results demonstrate that the hybrid ensemble-based framework outperforms individual classifiers, achieving high accuracy and consistent performance that includes both macro and micronutrients. This study also confirms the importance of considering both primary and secondary soil nutrients for reliable crop recommendation. By reducing dependency on traditional experiences with trial-and-error methods this study supports more informed decision-making and promotes efficient resource utilization for farmer.

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