Hybrid and Classical Machine Learning Models for Mixed-crop Recommendation in Precision Agriculture: An Empirical Performance Analysis

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Abstract. Precise mixed-crop recommendation is essential for increasing agricultural productivity, improving land utilization, and supporting sustainable farming. Effective crop combinations depend on several environmental and soil factors, making accurate recommendations a challenging task. This study compared classical and hybrid machine learning approaches for mixed-crop recommendation using an indigenous dataset from Andhra Pradesh, India. The dataset consisted of seven key features: nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall. The study evaluated Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), Decision Tree (DT), Logistic Regression (LR), Random Forest (RF), and Extra Trees (ET), alongside a proposed hybrid Random Forest-Extra Trees (RF-ET) model. Performance was measured using accuracy, precision, recall, F1-score, k-fold cross-validation, and confusion matrix analysis. The results show that the proposed hybrid RF-ET model achieved the best performance, obtaining 95.91% accuracy, 95.98% precision, 95.91% recall, and 95.94% F1-score. The model also demonstrated strong robustness through cross-validation. These findings indicate that hybrid machine learning can significantly improve the accuracy and reliability of mixed-crop recommendation systems, providing farmers with better decision-support tools for sustainable and efficient agricultural production.

Keywords: *classical; hybrid; machine learning; mixed-crop; NPK; precision agriculture; recommendation system.*

1 Introduction

Agriculture is an essential sector worldwide, and improving crop yields is essential to satisfy the needs of a growing population. Machine learning-based crop recommendation systems are widely applied across various domains of artificial intelligence research today. Several existing studies relied on classical machine learning algorithms for single-crop recommendations, many of which have weaknesses when compared to hybrid ML models in terms of accuracy. However, it is imperative to identify the most effective machine learning model among those models used [1]. This study proposed a free, open-source cloud-

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based ML platform for crop recommendations, compared five algorithms (KNN, DT, RF, XGBoost, SVM), and selected the best model to support precision farming adoption [2]. The proposed model uses SMOTE to balance the dataset and applies 13 different classifiers, including LR, DT, KNN, SVC, RF, and others, on a cloud-based dataset. In [3], the development of an ML approach for predicting farm output is presented. Crop yield estimation was conducted by collecting relevant data and training it using six different models [4]. The proposed technique was assessed using a publicly available Kaggle dataset, achieving outstanding performance. In [5], an effort is reported to improve soil analysis accuracy and speed using AI, DL, and ML, employing algorithms like RF, SVM, and NN with soil and environmental data. Similarly, in [6], a model was developed that combines optimization techniques with ensemble methods to improve prediction accuracy. Classifiers such as SVM, KNN, DT, and LR were compared with ensemble approaches like voting and stacking.

The major concerns with single-cropping are soil health, economic-instability, and risk of crop failure. Mixed-cropping is a reasonable and environmentally friendly choice because it supports farmers in attempting to achieve better soil health, lower crop risk, steadier income, and more resilience to climatic and market unpredictability.

In the present study, mixed-crop recommendation refers to the prediction of predefined crop combinations rather than individual crops. Each output label in the dataset represents a specific combination of crops that can be cultivated together under given soil and climatic conditions. These combinations are encoded as categorical class labels, where each class corresponds to a unique crop mixture.

In recent years, rapid advancement of data-driven technologies has significantly changed how decision-making is done in a variety of fields. Among these, machine learning has developed as a crucial means for predictive analytics, classification, and optimization tasks. The performance of machine learning models does not rely on just one factor, rather, it is firmly impacted by the size and quality of the dataset, the model architecture, and the specific problem it is applied to. Accordingly, selecting the most suitable model requires a systematic and careful comparison of several techniques. Comparative performance analysis makes it more expedient to comprehend the strengths and weaknesses of a variety of models and how suitable and strong they are for a particular task. By evaluating the models using accuracy, precision, recall, F1-score, and cross-validation, researchers and practitioners can make an informed choice. This technique assists them in balancing robust predictive performance with the efficient use of feasible resources. Such analysis is particularly essential in areas like agriculture, where

the trustworthiness of predictions can have a direct impact on real-world results, including crop productivity and resource management.

This study performed an experimental comparison of hybrid RF-ET model and classical machine learning models to assess their predictive performance for mixed-crop recommendation. Using a consistent experimental framework, a uniform dataset, and same evaluation metrics, the study's goal was to determine the most effectual model for mixed-crop recommendation in the Andhra Pradesh region in India and to offer experimental suggestion on the benefits of hybrid machine learning methods for agricultural decision-support systems. A hybrid RF-ET model is proposed and detailed in Subsection 3.4.7.

Unlike previous agricultural ensemble methods, which focused on single-crop recommendation, crop yield prediction, or optimization-assisted hybrid models, the proposed RF-ET framework is specifically designed for mixed-crop recommendation. By combining the complementary randomization mechanisms of Random Forest and Extra Trees through soft voting, the framework achieves improved robustness while retaining computational simplicity and interpretability. Furthermore, the study provides one of the first comprehensive evaluations of a hybrid ensemble model for multi-class mixed-crop recommendation using 36 crop-combination classes under region-specific agricultural conditions.

The objectives of this study were:

1. To evaluate ML techniques using key performance metrics and identify the most effective model for mixed-crop recommendation, thereby proposing guidance to experts and investigators on choosing the most fit algorithm.
2. To identify and analyze the strengths and weaknesses of various ML models in sustainable agriculture, highlighting their potential to boost mixed-crop yields, enhance food security.
3. Validation of the proposed hybrid ensemble model using a region-specific agricultural dataset.

2 Literature Review

Present studies in agricultural machine learning stress the need to improve prediction accuracy through advanced modeling approaches and optimization techniques. Approaches such as classical machine learning models demonstrate superior performance by effectively tuning hyperparameters. Supervised machine learning models that use soil and climatic data are broadly utilized for crop recommendation, though they frequently rely on historical datasets and may lack adaptability to changing conditions. In addition, feature extraction

approaches like Grey Level Co-occurrence Matrix (GLCM), combined with classifiers like AdaBoost, Decision Tree, ANN, and K-NN, have been applied to enhance prediction by integrating spatial and texture information. However, these techniques tend to improve computational complexity. Comparative studies have further revealed that choosing the most suitable model remains challenging due to dataset dependency and parameter sensitivity. Remote sensing approaches, comprising of multispectral and hyperspectral imaging, real-time sensing, IoT integration, AI-enabled analytics, and implementation challenges in digital agriculture have all been covered, along with smart sensor technologies in agricultural precision. This has provided valuable insight into crop health and yield prediction, but their practical application is limited by cost and data availability. Overall, while classical machine learning has shown strong potential in supporting data-driven agricultural decisions, many studies largely focused primarily on classical machine learning models [7]–[12].

In addition, in crop recommendation, data mining approaches have been used for relevant agricultural problems such as vegetable price forecasting, where environmental and economic factors including temperature, rainfall, fuel prices, and crop production are taken into consideration. Although these approaches expand the scope of ML in agriculture, they present additional complexity due to the dynamic and multi-factor nature of price variation. Similarly, advancements in remote sensing and satellite imagery, combined with DL and ML models like WA-CNN, RF, and SVM, have enabled precise large-scale crop classification. Despite their high accuracy, these approaches need important computational resources and access to high-quality datasets, which may limit their practical deployment [13]–[16].

Although they use different modeling techniques and data sources, models like RF, PR, and SVR have been widely applied to predict crop yields using key climate parameters like temperature and rainfall. While these approaches demonstrate resilient predictive ability, they are often limited by their reliance on a narrow set of input features, which may not fully capture the complexity of agricultural systems. More advanced techniques, such as hybrid optimization-integrated models (HMFO-ML), merge machine learning methods like Probabilistic Neural Networks and Extreme Learning Machines to improve both of crop recommendation and yield forecast. These models attain high accuracy but tend to improve computational complexity and decrease interpretability. Deep learning-based methods have also been explored for crop classification and management, offering improved performance in handling large and complex datasets. However, their dependence on large training data and high computational requirements may limit practical adoption, particularly in resource-constrained environments.

Hybrid frameworks integrating optimization techniques with DL models, such as WLSTM integrated with Swarm Optimization and IoT-based data acquisition, have shown improved capability in handling complex agricultural datasets through efficient feature selection and temporal modeling. While these approaches enhance prediction performance, they also introduce higher computational complexity and dependency on continuous data streams from IoT systems. Similarly, hybrid approaches merging recurrent neural networks (LSTM) for climate analysis with ensemble models like RF for crop recommendation offer enhanced predictive performance but enhance system complexity and decrease transparency. Regression-based techniques like LASSO continue to be utilized for crop yield prediction across diverse regions, presenting robustness and adaptability to structured datasets. Additionally, models using combined soil and climate features for crop recommendation present the importance of integrating multiple environmental parameters to improve decision-making accuracy [17]–[23].

Table 1 presents an in-depth evaluation of relevant previous work, highlighting limitations that highlight the need for more reliable and robust machine learning solutions in agriculture by comparing their datasets, techniques, and performance. In spite of technological advancement in crop recommendation systems, previous studies largely contributed to single-crop recommendation and classical machine learning techniques, limiting their capability to address the complexities of mixed-cropping. Furthermore, hybrid machine learning techniques remain underexplored and there is a need for comprehensive assessment on region-specific datasets. These limitations highlight the need for a strong comparative analysis of hybrid and classical ML models for mixed-crop recommendation.

Table 1 Comparative analysis summary of related existing studies.

Reference	Techniques used	Evaluation Metrics Used	Dataset	Performance	Limitations of Previous Studies
[1]	SVM	F1-score, recall, precision, accuracy, and K-fold cross validation	Agricultural Department of the Government of Rajasthan datasets	87.38%	The study predicts only one suitable crop from a set of crop categories
[2]	NB and SVM	Accuracy, precision and recall	Indian agriculture websites	92.56%	The comparison was limited to only two classical machine learning models
[3]	MLP	Precision, recall, accuracy, and confusion matrix	Data was gathered from five selected locations in Sri Lanka.	90.78%	The study compared individual deep learning models but did not investigate hybrid or ensemble approaches

Reference	Techniques used	Evaluation Metrics Used	Dataset	Performance	Limitations of Previous Studies
[4]	RF	Precision, accuracy, and recall	Data were collected from 30 districts in Karnataka, India	93.20%	Focused on single-crop recommendation based on seasonal and area-wise data. The study did not investigate hybrid frameworks that combine complementary models
[5]	Probabilistic Neural Network (PNN)	Correlation matrix, MSE, RMSE, MAE, and R-Square	Indian regional dataset	90.89%	Although the study compared several ML models for crop yield prediction, it did not explore hybrid ensemble approaches or mixed-crop recommendation systems
[6]	DT	Accuracy precision, recall and F1-score	Madurai, Tamil Nadu dataset	89.42%	This proposed model recommends only one suitable crop and classical ML models were evaluated
[7]	Kernel Ridge Regression (KRR)	MSE, MAE, and R-square	Bangladesh potato dataset	92.46%	This work recommends suitable potatoes based on specific soil and climate
[8]	RF	Accuracy, precision, recall and execution time (sec)	Indian Chamber of food and agriculture	93.39%	Utilized Random Forest for single-crop prediction but did not explore mixed-crop recommendation or hybrid ensemble models that leverage the strengths of multiple classifiers
[9]	RF	F1-score, recall, accuracy, and precision	Telangana State of India Dataset	92.20%	Although the study compared several ML models, it focused on recommending a single crop. The study did not investigate hybrid frameworks or mixed-crop recommendation systems that can better support diversified farming practices
[10]	DT	Confusion matrix, F1-score, recall, accuracy, and precision	Kaggle repository	90.80%	Concentrated on recommending a single crop from 22 crop classes using a generic dataset.

3 Materials and Method

This research work utilized an agricultural dataset acquired from the Indian Institute of Soil Science, Bhopal and integrated native soil and climate features of the Andhra Pradesh region. This soil attributes included are NPK and pH value while the climatic features included are temperature, humidity and rainfall. These features were carefully selected due to their vital impact on crop growth. Classical SVM, K-NN, DT, LR, RF and ET classifiers and hybrid RF-ET machine learning model were applied.

3.1 Dataset

The dataset utilized in this work was composed of 2552 records comprising 36 different varieties of crops. The dataset offers an in-depth foundation for testing and training the models of a mixed-crop recommendation system because every data point includes a variety of features, including soil nutrients and climatic conditions parameters. Each class in the dataset represents a predetermined mixed-crop combination and the dataset is presented as a multi-class classification task. In order to make sure equal distribution and suitability under specific soil and climatic conditions, labels were assigned based on agricultural suitability and professional knowledge. The dataset includes precise measurements from several agricultural seasons between 2021 and 2025. The dataset comprises 36 mixed-crop classes with a similar distribution in order to minimize class imbalance and ensure unbiased model training. Each class has approximately 66 and 74 samples. Figure 1 presents a sample from the dataset used for the mixed-crop recommendation system, demonstrating main soil and climate features.

	N	P	K	temperature	humidity	pH	rainfall	label
2548	140	14	350	22.107190	78.583201	6.364730	74.941366	cotton, soybean, pigeon pea
2549	160	18	400	23.038140	76.110215	6.913679	91.496975	cotton, soybean, pigeon pea
2550	180	22	450	24.547953	75.397527	7.766260	63.880799	cotton, soybean, pigeon pea
2551	200	26	500	23.738680	75.775038	7.556064	76.636692	cotton, soybean, pigeon pea
2552	220	30	550	22.318719	83.861300	7.288377	65.357470	cotton, soybean, pigeon pea

Figure 1 The dataset used for mixed-crop recommendation.

3.2 Data Pre-Processing

To arrange the dataset, outliers were removed, omitted values were handled, and anomalies were fixed. To guarantee steady scaling, numerical features were

normalized and categorical features were encoded. Redundant features were deleted, while related ones were carefully chosen using correlation and information-based techniques.

3.3 Training and Testing Models

Two partitions were created from the dataset, with 80% of the data applied for model training and the leftover 20% utilized for testing. The training set was utilized to learn the trends and relationships among input features and crop combinations, while the testing set was used to assess the generalization capability and to train the model performance on unobserved data.

3.4 Model Selection

3.4.1 Support Vector Machine (SVM)

SVM builds an optimum decision boundary that splits different crop suitability classes with a maximum margin. It is effective in handling high-dimensional agricultural data and model complexity, non-linear relationships among soil nutrients, climate conditions, and crop compatibility using kernel functions.

3.4.2 K-Nearest Neighbor (K-NN)

K-NN is a distance-based technique that recommends crop combinations based on the resemblance between new farm conditions and historic records. The model assigns a class by analyzing the common class among the ‘k’ most similar data points.

3.4.3 Decision Tree (DT)

DT builds a tree-like framework of rules by splitting the data repeatedly on the most informative attribute. It offers clear and interpretable decision paths.

3.4.4 Logistic Regression (LR)

LR is used to assess the suitability for diverse crop combinations by modeling the relationship within the input features and categorical output categories. It is computational effective and functions as a strong baseline model for comparing the performance of more complex and hybrid approaches.

3.4.5 Random Forest (RF)

RF builds several decision trees and merges their results to make more accurate predictions.

3.4.6 Extra Trees (ET)

ET builds many randomized decision trees and incorporates their results to make final predictions.

3.4.7 Random Forest–Extra Trees (RF–ET)

RF–ET is a hybrid approach that combines many randomized decision trees, which increases generalization and decreases overfitting. This hybrid technique captures complex non-linear relationships among soil and climatic features, making it more resilient to outliers and noise, and automatically classifies important factors. The proposed RF-ET hybrid model integrates Random Forest and Extra Trees to improve performance and generalization. Both models are tree-based but differ in their randomness mechanisms. Random Forest uses bootstrap sampling and feature selection for randomness. Extra Trees brings extra randomness using random split selection without bootstrapping.

The proposed hybrid model integrates each of the models by applying a soft voting technique. The final prediction is computed by averaging the predicted probability from all the models. This technique enhances complete classification accuracy, decreases variation, and strengthens robustness. The importance of the hyperparameters for each model were carefully chosen based on experimental assessment. For Random Forest, the minimum samples per split (min_samples_split) was set to 2, the maximum tree depth (max_depth) to 10, and the number of trees (n_estimators) to 100. Random split selection was enabled for Extra Trees, with n_estimators set to 100, max_depth to 10, and min_samples_split to 2. To assure standardized and frequent tests, the models were developed in Python using Scikit-learn, NumPy and Pandas for preprocessing and analysis.

3.5 Model Evaluation

The model evaluation validated that it can perform well with unobserved data rather than simply memorizing the training set. Secondly, it provides intuitions into how the model's predictive performance can be improved by fine-tuning hyperparameters or transforming the learning algorithm. Lastly, the evaluation supports pinpointing the most suitable model for addressing a specific problem, thereby guiding practitioners and researchers toward more trustworthy and competent solutions. It is emphasized that model performance was assessed through six key metrics: its performance, the process of model selection, and comparison with other models.

3.5.1 Accuracy

Accuracy is an essential performance metric in machine learning, representing the proportion of accurately predictions to the complete predictions prepared. It shows how often the model suitably classifies or predicts outcomes, as expressed in Eq. (1).

$$\textbf{Accuracy} = \frac{\textbf{(TP) True Positives+(TN) True Negatives}}{\textbf{TP+TN+FP+FN}} \tag{1}$$

3.5.2 Precision

Precision is an evaluation metric that evaluates the accuracy of correct predictions. It represents the percentage of precisely predicted occurrences that are correct, indicating the model's reliability when classifying an outcome as positive, as expressed in Eq. (2).

$$\textbf{Precision} = \frac{\textbf{(TP) True Positives}}{\textbf{(TP)True Positives +(FP) False Positives}} \tag{2}$$

3.5.3 Recall

Recall is a performance metric that analyze a model's ability to suitably classify all actual positive cases in a dataset. It reflects how well the model captures relevant positives without overlooking them, as expressed in Eq. (3).

$$\textbf{Recall} = \frac{\textbf{(TP) True Positives}}{\textbf{(TP) True Positives +(FN) False Negatives}} \tag{3}$$

3.5.4 F1-Score

Recall and precision were integrated into an individual balanced statistic; this is mainly helpful when evaluating models on unbalanced datasets where accuracy could be inaccurate, as expressed in Eq. (4).

$$\textbf{F1 - Score} = 2 * \frac{\textbf{Precision*Recall}}{\textbf{Precision+Recall}} \tag{4}$$

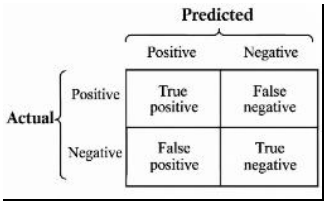
3.5.5 K-Fold Cross-Validation

K-Fold Cross-Validation is a model evaluation approach used to measure a machine learning algorithm's ability to adapt to new or unobserved data, as expressed in Eq. (5).

$$\text{Mean accuracy} = \frac{1}{k}\sum_{i=1}^{k} Ai \quad \text{where} \quad \text{standard deviation } \boldsymbol{\sigma} = \sqrt{\frac{1}{\text{k}-1} = \sum_{i=1}^{k}(Ai - \mu)2} \tag{5}$$

3.5.6 Confusion Matrix

The confusion matrix is a tabular tool used to measure the performance of a classification model by relating predicted class labels with actual ones. It offers a comprehensive analysis of accurate and inaccurate predictions for individual classes, enabling the identification of robustness and faults in the model's classification performance.



4 Results

The performances were assessed of six classical machine learning approaches (SVM, K-NN, DT, LR, RF, ET and the proposed hybrid RF-ET model) for mixed-crop recommendation. The models were trained and tested with soil and climate parameters. All performance metrics were tested and compared by utilizing equal experimental conditions. Figure 2 presents the proposed mixed-crop recommendation system, which was developed and executed using Python-based libraries.

```
In [ ]: crop_app = joblib.load('crop app')

In [ ]: crop_arr = [[200, 100, 100, 30, 500, 1.50, 46]]

In [ ]: hybrid_preds = crop_app.predict(crop_arr)

C:\Users\AHMED GIMBA\anaconda3\Lib\site-packages\sklearn\base.py:
sifier was fitted with feature names
  warnings.warn(

In [ ]: hybrid_preds

Out[ ]: array(['maize', 'cowpea', 'groundnut'], dtype=object)
```

Figure 2 The proposed hybrid RF-ET recommendation model.

Table 2 presents the implementation results of conventional machine learning techniques SVM, K-NN, DT, LR, RF and ET on the same dataset, with their performances compared to the proposed hybrid RF-ET model, which achieved the highest accuracy of 95.91%.

Table 2 Performance comparison of several models using the same dataset.

Models	Accuracy	Precision	Recall	F1-Score
SVM	86.69%	91.40%	84.61%	87.88%
K-NN	75.15%	77.65%	75.75%	76.69%
DT	90.99%	92.13%	92.25%	92.19%
LR	74.16%	77.66%	74.74%	76.17%
RF	93.85%	94.10%	93.80%	93.95%
ET	94.32%	94.50%	94.20%	94.35%
Proposed RF-ET	95.91%	95.98%	95.91%	95.94%

To additionally validate the efficiency of the proposed hybrid model, standalone Random Forest (RF) and Extra Trees (ET) models were assessed under the same experimental conditions. As shown in Table 2, both RF and ET achieved strong performance; however, the hybrid RF-ET model outperformed them in all evaluation metrics. This illustrates how pairing the complimentary qualities of RF and ET enhances predictive performance.

Table 3 presents the complete evaluation metrics and class-wise performance analysis that was done to evaluate the efficiency of the proposed RF-ET model across individual mixed-crop combinations. This is mainly important for multi-class classification problems, where aggregate metrics may not completely replicate model behavior for each class.

Table 3 Class-wise performance of the RF-ET Model.

Classes	Precision	Recall	F1-Score
Class-1	0.96%	0.95%	0.95%
Class-2	0.95%	0.96%	0.95%
Class-3	0.96%	0.96%	0.96%
Class-4	0.95%	0.94%	0.94%
Class-5	0.97%	0.96%	0.96%
...	...	...	...
Class-36	0.97%	0.96%	0.96%

The class-wise results show that the proposed hybrid RF-ET model consistently attained high performance throughout all crop combinations, with precision, recall, and F1-scores ranging within 0.94% and 0.97%. Slight disparities were observed in certain classes due to differences in feature distribution and class separability. All reported precision, recall, and F1-score values were computed using weighted-average technique to account for class distribution.

Figure 3 demonstrate the proposed RF-ET model outperformed all other machine models, which were compared by measuring accuracy, precision, recall, and F1-score.

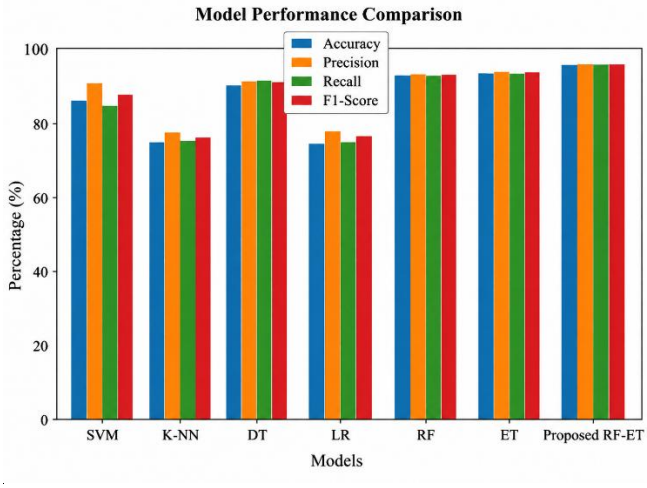


Figure 3 Performance comparison of several models using the same dataset.

Figure 4 shows the confusion matrix of the hybrid RF-ET model, presenting a high number of correctly classified occurrences, thus showing strong predictive performance.

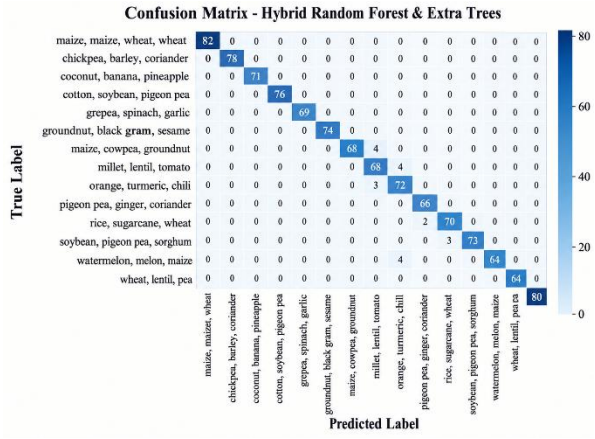


Figure 4 Confusion matrix of the hybrid RF-ET model.

The stability of the model was assessed using ten-fold cross-validation. Ten subsets of the dataset were generated while on each model iterative training and testing was performed. The mean accuracy result illustrates the stability and applicability of the proposed hybrid RF-ET model by representing the mean performance over all folds along with the related standard deviation. Table 3

presents the proposed RF-ET model, which achieved the highest mean accuracy with the lowest standard deviation among all evaluated models.

Table 4 Ten-fold cross-validation performance of the models.

Model	Mean Accuracy %	Standard Deviation	K
SVM	86.69% ± σ	±0.8	10
K-NN	75.15% ± σ	±1.1	10
DT	90.99% ± σ	±0.6	10
LR	74.16% ± σ	±1.2	10
RF	93.93% ± σ	± 0.3	10
ET	94.34% ± σ	± 0.2	10
Proposed RF-ET	95.91% ± σ	±0.4	10

To further validate the superiority of the proposed RF-ET model, paired t-tests were conducted using the accuracies obtained from ten-fold cross-validation. The results showed that RF-ET significantly outperformed SVM ($p = 0.000044$), K-NN ($p = 0.000002$), DT ($p = 0.0085$), LR ($p < 0.000001$), and ET ($p = 0.000044$). However, the performance difference between RF-ET and RF was not statistically significant ($p = 0.591$), indicating that both models achieved comparable predictive performance. These results provide additional statistical evidence supporting the effectiveness and robustness of the proposed hybrid RF-ET framework for mixed-crop recommendation. Table 4 shows the statistical significance t-test result.

Table 5 Paired t-test performance comparison analysis of the models.

Comparison	t-statistic	p-value	Significance (α = 0.05)
RF-ET vs SVM	7.331	0.000044	Significant
RF-ET vs K-NN	10.508	0.000002	Significant
RF-ET vs DT	3.354	0.008475	Significant
RF-ET vs LR	22.916	2.73×10^{-9}	Significant
RF-ET vs RF	0.557	0.591175	Not significant
RF-ET vs ET	7.342	0.000044	Significant

Feature importance was computed by applying the mean decrease in impurity (MDI) obtained from both Random Forest and Extra Trees models. A hybrid importance score was computed by averaging the important scores from the two models, which were ultimately normalized. Temperature (0.221), rainfall (0.189), and nitrogen (0.172) were shown to be the most important features influencing mixed-crop recommendation, as indicated in Table 5 and Figure 5. This shows that the availability of nutrients in the soil and climate have an important impact on the best crop combinations.

Table 6 Model-derived feature importance using Hybrid RF-ET (MDI method).

Feature	RF Importance	ET Importance	Hybrid RF-ET Importance	Normalized Importance
Temperature	0.214	0.228	0.221	0.221
Rainfall	0.192	0.185	0.189	0.189
Nitrogen (N)	0.176	0.168	0.172	0.172
Humidity	0.143	0.136	0.140	0.140
Potassium (K)	0.112	0.105	0.109	0.109
Phosphorous (P)	0.098	0.092	0.095	0.095
pH	0.065	0.058	0.062	0.062

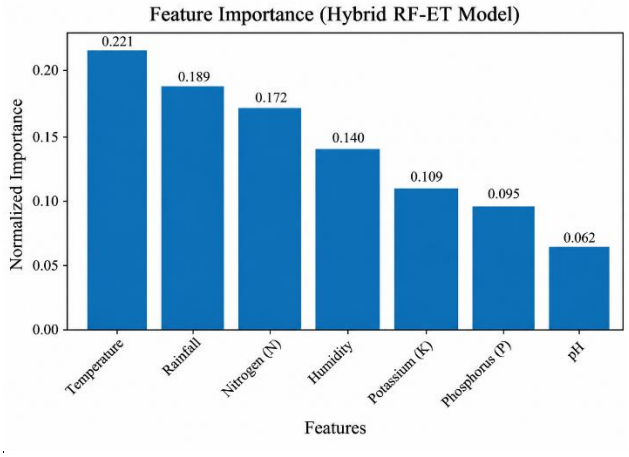


Figure 5 Feature importance of the Hybrid RF-ET model.

5 Discussion

This work explored the application of machine learning models for mixed-crop recommendation, with a specific emphasis on the soil and climate surroundings of Andhra Pradesh, India. A comprehensive comparative analysis was carried out across several classical machine learning models, i.e., SVM, K-NN, DT, LR, RF and ET, to evaluate their efficacy in predicting the best suitable mixed-crops for cultivation. A novel hybrid approach that combines Random Forest (RF) and Extra Trees was introduced and evaluated against these classical models in order to improve predictive performance. With an accuracy of 95.91%, the findings of the experiment clearly show that the recommended RF-ET hybrid model consistently surpasses the performance of the individual classical machine learning approaches. In addition, the hybrid RF-ET model proved its robustness and stability as a successful technique for mixed-crop recommendation in region-

specific agricultural development by outperforming others in terms of accuracy, precision, recall, F1-score, and k-fold cross-validation.

The superior performance of the Hybrid RF-ET model compared to its individual components (RF and ET) confirms the advantage of ensemble hybridization in extracting complex relationships within agricultural data.

By integrating predictions from various decorrelation-related decision trees, Random Forest's (RF) superior performance contributed to boost predictive accuracy, which reduced variance. On the other hand, Extra Trees provided extra randomness in feature selection and split threshold, allowing the model to explore a wider feature space and decrease overfitting. The hybrid model strengthened generalization and better base-learner mixture by incorporating RF-ET.

The proposed hybrid RF-ET model's feature-driven insight has direct practical application in mixed-cropping systems. The dominance of temperature, rainfall, and nitrogen (N) as important predictors shows that crop suitability among crops is mainly influenced by availability of nutrients in the soil and climatic-related interactions. This makes it feasible to identify complimentary pairs of crops with different growth dynamics and nutrient uptake patterns in mixed cropping. While the proposed hybrid RF-ET model indicates higher predictive performance under controlled experimental settings, these findings are limited to the dataset and evaluation framework used in this study. The applicability of the model in real-world agricultural conditions, like on-field implementation or integration into advisory systems, needs to be validated. Therefore, the reported improvements should be interpreted as proof of model ability rather than confirmed practical impact.

Despite the promising performance of the proposed RF-ET framework, this study was limited by the use of a single region-specific dataset collected from Andhra Pradesh, India. Agricultural conditions vary significantly across regions due to differences in climate, soil composition, cropping patterns, and management practices. Consequently, the Hybrid RF-ET model's performance may differ when applied to other geographical locations. Therefore, caution should be exercised when generalizing the findings beyond the study area. Future research should validate the proposed framework using multi-regional datasets and real-world field deployments to evaluate its robustness, adaptability, and scalability under diverse agricultural conditions.

6 Conclusion

This paper demonstrated experiments to evaluate and benchmark the performance of six classical machine learning techniques: SVM, K-NN, DT, LR,

RF, ET and the proposed Hybrid RF-ET ML model, all evaluated using a mixed-crop recommendation dataset. The most effective model was then identified by preparing a comparative evaluation. When contrasted with classical machine learning techniques, the results showed that the proposed RF-ET hybrid machine learning model achieved the highest accuracy of 95.91%. Machine learning approaches were used to evaluate the mixed-crop recommendation dataset. The different algorithms were evaluated using commonly utilized performance measures, comprising accuracy, precision, recall, F1-score, k-fold cross-validation, and confusion matrix.

The proposed framework supports farmers who want to reduce uncertainty, improve farmland utilization, increase yields, and make sustainable farming decisions by offering them with reliable and flexible mixed-crop recommendations that perform well in a variety of farmland conditions. For farmers and policymakers, the proposed Hybrid RF-ET mixed-crop recommendation model can be an insightful decision-support tool. It is recommended that agricultural extension services incorporate the model into digital advisory platforms to offer data-driven, region-specific mixed-cropping recommendations.

A key limitation of this work was that the model was assessed using a region-specific dataset, which may limit its generalizability through different agro-climatic conditions. Future work should give emphasis on validating the model using different regional datasets and real-world agricultural scenarios and integrating Explainable Artificial Intelligence (XAI) techniques that will improve transparency and visual clarification in the model's decision-making, thus building trust while encouraging more effective proactive maintenance strategies.

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