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Research Article

Interpretable Machine Learning Techniques for an Advanced Crop Recommendation Model

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Achieving sustainable agricultural advancements necessitates optimizing crop yields while maintaining environmental stewardship. Our research addresses this critical imperative by introducing an innovative predictive model that refines crop recommendation systems through advanced machine learning techniques, specifically random forest and SHapley Additive exPlanations (SHAP). This study aims to overcome the limitations of traditional advisory approaches by incorporating interpretability tools, clarifying the model's decision-making process around specific instances. To enhance the model's local interpretability, we incorporated local interpretable model-agnostic explanations (LIMEs), providing transparent explanations for each crop recommendation, which fosters user trust, particularly when predictions diverge from established expert opinions. We conducted our empirical investigation using a comprehensive dataset that includes various agricultural parameters, historical crop yields, and environmental conditions to evaluate the model's performance. Our findings indicate a significant improvement in predictive accuracy over traditional methods. The application of SHAP values offers a groundbreaking analysis of feature importance, enabling a precise quantification of the contributions of factors such as soil quality, climatic variables, and historical crop performance to the predictive outcomes. This research advances the field of precision agriculture by presenting a model that excels not only in accuracy but also in providing actionable insights through enhanced interpretability. By balancing advanced predictive capabilities with user-centric explanations, our model represents a substantial step forward in developing data-driven, transparent, and trustworthy agricultural advisories.

Keywords: crop recommendation; LIME; machine learning; precision agriculture; random forest; Shapley values

1. Introduction

Modern agriculture faces the dual challenge of sustaining a growing global population while optimizing resource utilization. Crop recommendation systems have emerged as essential tools to assist farmers in making informed decisions tailored to their specific agricultural conditions. While machine learning techniques have significantly enhanced the accuracy of these systems, the challenge of interpretability remains a persistent concern [1].

Traditional crop recommendation models often rely on complex machine learning algorithms, such as neural networks and ensemble methods, which, despite their high predictive accuracy, are often opaque and lack transparency. This opacity can hinder their acceptance and adoption within the agricultural community. In practical applications, farmers and agricultural experts not only require accurate predictions but also demand clear explanations for the model's recommendations. An interpretable model is crucial as it allows stakeholders to understand the critical factors influencing crop recommendations and provides a rationale for specific predictions.

To address these challenges, we propose an explanatory predictive model for crop recommendation that integrates machine learning, SHapley Additive exPlanations (SHAP), and local interpretable model-agnostic explanations (LIME)

[2]. Our approach utilizes machine learning algorithms to deliver accurate and reliable predictions for optimal crop selection. Incorporating SHAP values enables the assessment of each feature's significance within the model, offering clarity on the factors that impact the recommendation results. In addition, LIME enhances the model's interpretability by providing specific explanations for each crop suggestion.

The recent research underscores the increasing focus on crop recommendation systems and the importance of interpretability in machine learning models. For instance, CropNet, a deep learning framework, has been proposed for crop recommendation, highlighting the need for interpretable approaches. Similarly, studies have emphasized the value of SHAP for their interpretability [3, 4]. The importance of trust in model predictions has also been highlighted, aligning with our goal to enhance the transparency of crop recommendation models [5].

In this study, we build upon these insights to develop an explanatory predictive model that achieves high accuracy while providing clear and understandable explanations for the recommendations. By integrating advanced machine learning techniques with interpretability tools, our model aims to balance predictive performance with transparency, ultimately contributing to more trustworthy and user-friendly agricultural advisory systems.

2. Literature Review

In recent years, there has been considerable focus on crop recommendation systems due to their potential to improve agricultural productivity and promote sustainable farming practices. This section offers a review of the existing literature on crop recommendation methods, the significance of interpretability in machine learning, and the application of Shapley values and LIME in agricultural decision-making.

Several crop recommendation approaches have been proposed in the literature, ranging from traditional statistical models to advanced machine learning techniques. For instance, the authors in [6] introduced CropNet, a deep learning framework for crop recommendation that demonstrated improved accuracy compared to conventional methods. In addition, the authors in [7] presented an interpretable approach using Shapley values, providing transparent crop recommendations and facilitating user understanding of the factors influencing the model's predictions.

Understanding machine learning model decisions has become a critical research area, particularly in domains with substantial impacts on human well-being. The authors in [8] introduced LIME as a technique that makes complex models more understandable by providing clear, localized interpretations. The versatility of LIME extends to various fields, including agriculture, where it provides users with transparent insights into model predictions [9].

The utilization of Shapley values, originating from cooperative game theory, has expanded to machine learning to quantify feature importance and enhance the understanding of model predictions [10]. In the context of agricultural decision-making, Shapley values played a crucial role in assessing the impact of various factors, such as soil characteristics, weather conditions, and historical crop performance, on recommendation outcomes [11]. Furthermore, LIME has been applied to provide localized explanations for individual crop recommendations, enabling farmers to validate model outputs and gain insights into the rationale behind specific predictions [12].

In addressing the challenge of optimizing rotating disc contactors (RDCs) for liquid–liquid extraction, a notable study has leveraged the random forest (RF) regression model enhanced by LIME. This innovative method not only achieves accurate drop size prediction but also sheds light on the interpretability issue, revealing how various factors and their interactions impact the outcome. Such integration marks a significant advancement in process optimization, offering insights into more effective RDC design and operation [13].

Examining the literature on crop recommendation systems highlights the importance of interpretable models for establishing user trust and acceptance. The application of Shapley values and LIME in agriculture provides a transparent and user-friendly method to understand the factors influencing crop recommendations. This empowerment facilitates informed decision-making for farmers. In the following sections, we present our proposed explanatory predictive model for crop recommendation, building upon insights from the literature review.

3. Methodology

This section details the methodology for developing an explanatory predictive model for crop recommendation. We employed the RF algorithm to analyze key factors such as nitrogen, phosphorus, potassium, soil pH, rainfall, temperature, and humidity that influence crop selection. The workflow depicted in Figure 1 includes data preprocessing, model training, and the application of SHAP and LIME for enhanced interpretability.

Initially, we aggregated a comprehensive dataset encompassing environmental and soil variables that affect crop viability. Following this, we preprocessed the data to ensure it was suitable for the analysis. The cleaned data were then input into the RF model to generate crop predictions.

A central aspect of our methodology is the focus on interpretability, as depicted in the diagram. We used Shepley values to measure the contribution of each feature to the model's output, identifying the most influential factors in the prediction process. This transparency is vital, as it helps farmers understand the basis of the recommendations, thereby building trust in the model's outputs.

LIME was incorporated to provide localized explanations, elucidating the influence of features on specific predictions. This dual approach—using both SHAP and LIME—facilitates model validation and ensures that recommendations are customized to individual conditions, reflecting the diversity in agricultural environments. Together, these tools transform the machine learning model into an insightful resource, offering clear and actionable crop recommendations. This methodology supports data-driven

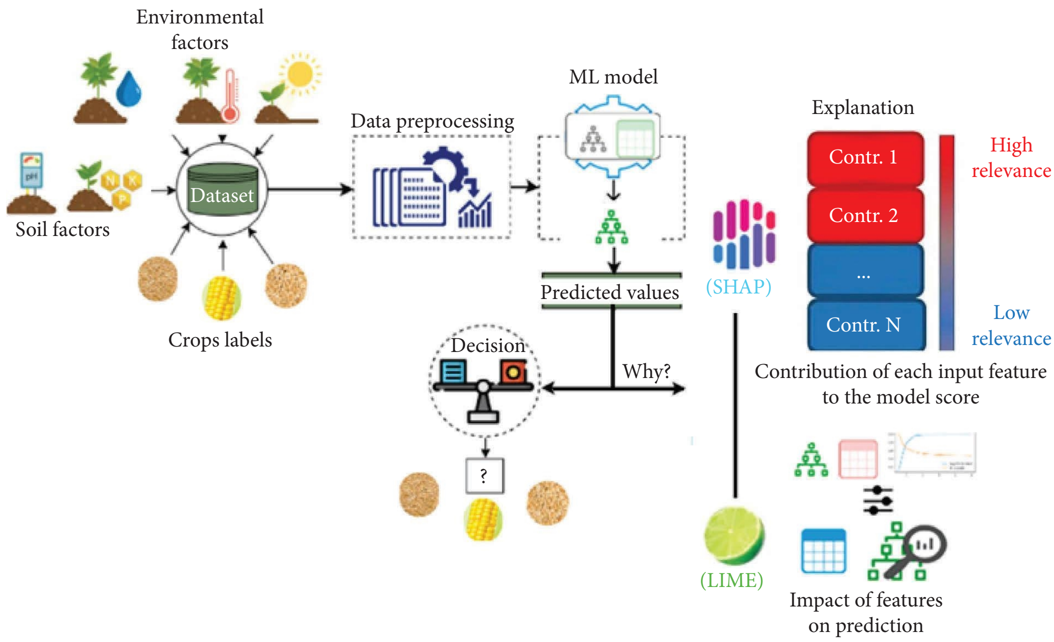

Figure 1: Comprehensive workflow of the proposed machine learning model.

agricultural practices, enhancing both productivity and sustainability.

3.1. Data Collection. The datasets utilized in this study, as illustrated in Tables 1 and 2, include crucial attributes representing agricultural parameters. These variables consist of N, representing the ratio of nitrogen content in the soil; P, indicating the ratio of phosphorous content; and K, denoting the ratio of potassium content. Temperature is measured in degrees Celsius, humidity is expressed as relative humidity in percentage, and pH signifies the soil's acidity or alkalinity. Rainfall is recorded in millimeters, and the label encompasses various types of crops, serving as the ground truth for model training and evaluation. With a total of eight attributes, these measurements offer a comprehensive overview of the environmental conditions influencing crop recommendations in the crop recommendation dataset, which comprises 2200 samples across 22 distinct crop types. This extensive dataset forms the foundation for implementing the RF algorithm and integrating Shapley values and LIME to develop an explanatory predictive model for accurate and interpretable crop recommendations.

3.2. Data Preprocessing Steps. Data preprocessing stands as a crucial stage in refining the initial agricultural dataset, creating an environment suitable for an effective analysis and modeling in the realm of crop recommendations. This pivotal step encompasses various processes aimed at elevating the quality and pertinence of the data.

- Data cleaning: Identifying and rectifying any missing or inconsistent values. Missing values were handled using imputation techniques, ensuring a complete dataset.

Table 1: Detailed attributes of the crop recommendation dataset.

Attributes	Values
Source	Crop recommendation
Number of samples	2200
Attributes	8
Usage	Classification
Label count	22

Table 2: Description of parameters used for crop recommendations.

Variable attributes	Description values
N	Nitrogen content ratio in soil
P	Phosphorus content ratio in soil
K	Potassium content ratio in soil
Temperature	Temperature measured in degrees Celsius
Humidity	Relative humidity percentage
pH	Soil pH level
Rainfall	Rainfall measured in millimeters
Label	Variety of crop types

- Outlier detection and removal: Detecting and removing outliers to prevent distortion in model training and predictions.
- Normalization: Normalizing the data to ensure all features contribute equally to the model's performance.

3.3. RF Model. The RF model illustrated in Figure 2 serves as a robust and versatile tool in the domain of crop recommendation. Comprising an ensemble of decision trees, this model excels in handling complex relationships within agricultural datasets. The individual trees collectively contribute to a powerful predictive framework, with each tree making independent predictions. Through a process of

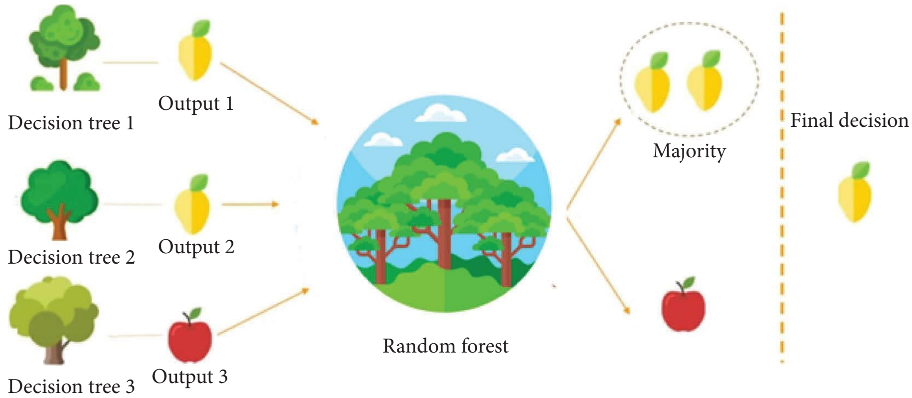

Figure 2: Structure and workflow of the random forest model.

bagging, where multiple trees are trained on different subsets of the data and feature randomization, RF mitigates overfitting and enhances generalization to new data. Its adaptability to diverse datasets and ability to capture nonlinear patterns make it a well-suited choice for predicting optimal crop choices based on a range of agricultural parameters. The ability of the RF model to deliver accurate and interpretable recommendations makes it a valuable tool for optimizing agricultural practices and achieving sustainable yields.

3.4. Hyperparameter Tuning and Model Validation

3.4.1. Hyperparameter Tuning. We conducted hyperparameter tuning using cross-validation techniques to optimize the model's performance. Key parameters adjusted included the number of trees in the forest, the maximum depth of the trees, and the minimum samples required to split a node.

3.4.2. Model Validation. The dataset was split into an 80:20 ratio, with 80% used for training and 20% for testing. Cross-validation was employed to assess the model's performance, ensuring robustness and reliability.

3.5. Model Evaluation. In our evaluation of model overfitting, we utilized validation curves to gain insight into how hyperparameter adjustments influence model performance. Validation curves are instrumental in visualizing the trade-offs between model complexity and performance metrics on both training and validation datasets. By systematically varying key hyperparameters and plotting the resulting training and validation scores, we were able to identify any significant discrepancies between the two sets. This approach allows us to detect overfitting if the model shows high performance on the training data but underperforms on the validation data as parameters change. By employing this method, we ensure a thorough assessment of the model's ability to generalize and avoid overfitting, providing a more nuanced understanding of its performance across diverse data scenarios.

3.6. Feature Importance With Shapley Values. Shapley values, derived from cooperative game theory and widely applied in machine learning, play a crucial role in attributing contributions to individual features in predictive models [14]. Consider a feature set $N = \{1, 2, \ldots, n\}$ and a predictive model, f, operating on an input vector $x \in X$, where X is the feature space.

3.6.1. Coalition. In Shapley values, a coalition, S, represents a subset of features from N, with its cardinality denoted as $|S|$.

3.6.2. Marginal Contribution. The marginal contribution of feature i to coalition S, denoted as $\Delta\Phi_i(S)$, is the difference in the model's output when feature i is added to coalition S, compared to the output without feature i. Mathematically, it is defined as

$$\Delta\Phi_i(\mathrm{S}) = \Phi(S \cup \{i\}) - \Phi(S). \tag{1}$$

3.6.3. Shapley Value for Feature i. The Shapley value, Φ_i, for feature i is the average of its marginal contributions across all possible feature coalitions. It signifies the expected contribution of feature i across all permutations of the feature set N. The Shapley value for feature i is given by the following equation:

$$\Phi_{\mathrm{i}} = \frac{\sum_i \Delta\Phi_i(S)}{n!}. \tag{2}$$

The sum is taken over all possible subsets S of N that do not contain feature i, and n is the total number of features.

Shapley values provide a fair and consistent way to attribute feature importance in the presence of interactions between features. They offer valuable insights into the contribution of each feature towards the final prediction of the model [15].

We employed the Shapley value technique to quantify each feature's importance in the RF model. By calculating the Shapley values for each input feature, we determined the contribution of nitrogen, phosphorus, potassium, soil pH, rainfall, and humidity to the model's predictions. The Shapley values provide a fair and consistent way to attribute the importance of each feature in the presence of interactions between them.

3.7. Local Interpretability With LIME. To enhance local interpretability, we incorporated the LIME technique into our model. LIME produces simplified interpretable surrogate models tailored to individual crop recommendations. Specifically, for each unique crop recommendation, LIME constructs a surrogate model that simplifies the behavior of the RF model within the local vicinity. This surrogate model effectively highlights the influence of each feature on the recommended crop, providing a comprehensible explanation for the prediction.

Consider the following components:

The original complex black-box model is denoted as $f(x)$, where x represents the input vector.

The local linear model is represented by $g(x)$.

LIME's objective is to approximate the black-box model $f(x)$ with a more straightforward local linear model $g(x_0)$, where x_0 is the instance of interest. The local linear model is trained to mimic the behavior of the black-box model in the neighborhood of x_0.

3.7.1. Proximity Measure (Kernel Function). LIME initiates by defining a neighborhood around the instance of interest, x_0, using a proximity measure, often expressed as a kernel function $K(x, x_0)$. This kernel function quantifies the similarity between x and x_0, with commonly used options including Gaussian kernels and exponential kernels [16].

3.7.2. Local Linear Model. Within the neighborhood, LIME gathers a dataset D comprising perturbed samples and their corresponding predictions from the black-box model f. These perturbed samples are randomly drawn from the distribution defined by the kernel function around x_0, introducing local randomness. The local linear model, $g(x)$, is then trained on this dataset D and typically takes the form of a linear model with interpretable coefficients.

3.7.3. Model Interpretation. The coefficients of the local linear model, $g(x)$, serve as local explanations for the instance x_0. These coefficients signify the contribution of each feature to the prediction made by the black-box model for the specific instance x_0. The magnitude and sign of each coefficient indicate the impact of the feature on the black-box model's prediction for that particular instance.

By interpreting the coefficients of the local linear model, LIME provides human-understandable explanations for the predictions of the complex black-box model in the vicinity of the instance of interest. This contributes to users' understanding of why the model made a specific prediction, thereby enhancing transparency and trust in AI systems.

In the agricultural domain, LIME helps bridge the gap between complex machine learning models and end-users, such as farmers or agricultural experts. It provides localized explanations for individual crop recommendations, offering clarity on why a certain decision was made. This increased interpretability contributes to user trust and acceptance, particularly in scenarios where model predictions may deviate from expected outcomes.

3.8. Model Evaluation. We assessed the performance of our explanatory predictive model using standard metrics, incorporating metrics such as mean accuracy, precision, recall, and the $F1$ score. The model's accuracy in predicting crop yields and the consistency of feature importance values derived from Shapley values were examined. In addition, we conducted a comparative analysis of our model's interpretability against traditional black-box models, highlighting the advantages of our proposed approach.

To outline the methodology, we employed the RF algorithm to analyze the influence of nitrogen, phosphorus, potassium, soil pH, rainfall, and humidity on crop recommendations. Through the integration of Shapley values and LIME, our model offers transparency and interpretability, providing farmers and agricultural experts with actionable insights to make well-informed crop decisions. In the subsequent section, we detail our experimental findings and explore the consequences of our interpretative predictive framework for crop suggestion.

4. Experiments and Results

In this section, we detail the experimental configuration, assessment criteria, and outcomes of our explanatory predictive model designed for crop recommendation. We conducted comprehensive experiments utilizing the RF algorithm, taking into account variables such as nitrogen, phosphorus, potassium, soil pH, rainfall, and humidity to forecast appropriate crops under diverse agricultural conditions. Figure 3 shows our workflow for the crop recommendation system. The methodology encompasses a rigorous experimental framework, assessing the efficacy of nutrient and weather parameters in determining optimal crop choices, thus offering a strategic tool for decision-making in diverse farming contexts. The outcomes underscore the model's robust capability to navigate complex agricultural ecosystems, providing a data-driven guide for crop selection.

4.1. Experimental Setup. The dataset underwent an 80-20 split, dividing it into training and testing sets, ensuring a consistent distribution of crops and environmental parameters in both groups. The RF model underwent training on the designated training set, and hyperparameter fine-tuning occurred through cross-validation techniques to enhance its performance. Shapley values for feature importance and LIME explanations were calculated on a distinct validation set.

4.2. Evaluation Metrics. In Table 1, various machine learning models are evaluated based on a suite of performance metrics to determine the most suitable model for a classification task. The metrics used for comparison are as follows:

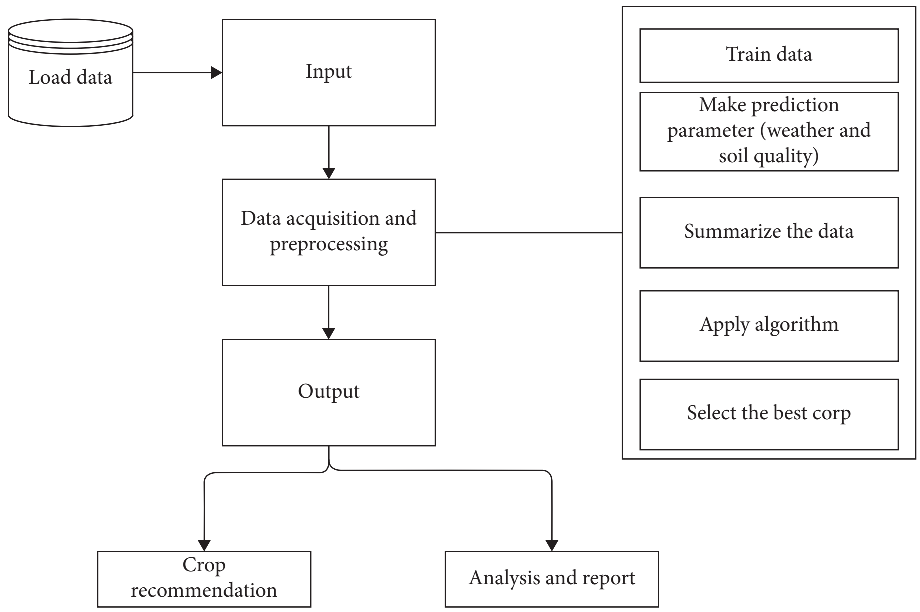

Figure 3: Proposed methodology for crop prediction and recommendation.

- Accuracy: The proportion of correct predictions over the total number of cases evaluated. High accuracy indicates a model's overall ability to correctly label all classes.
- Precision: The ratio of true positive predictions to the total number of positive predictions made. High precision indicates a low rate of false positives.
- Recall: Also known as sensitivity, it measures the proportion of actual positives correctly identified. High recall indicates a model's ability to capture most positive instances.
- $F1$ score: The harmonic means of precision and recall, providing a balance between the two. A high $F1$ score indicates a model with a good balance of precision and recall.

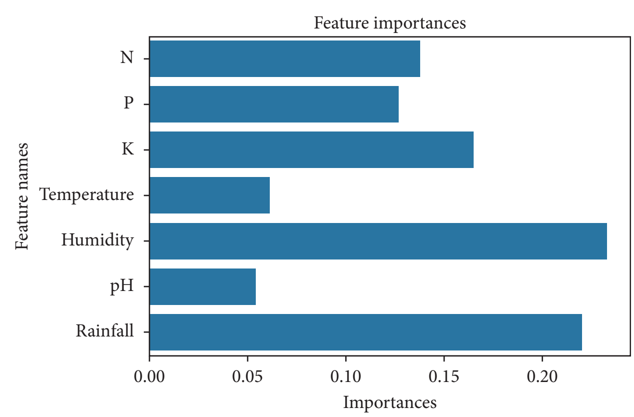

Figure 4: The importance of multiple factors ranking of climatic and soil parameters.

4.3. Results

4.3.1. Feature Importance in Agricultural Predictive Model. Figure 4 provides a visual representation of the relative importance of various climatic and soil features used in an agricultural predictive model. The importance values are likely derived from a machine learning algorithm that has been trained to predict agricultural outcomes, such as crop yield or suitability. From Figure 4, it is evident that "rainfall" holds the highest importance among the features, suggesting that precipitation levels have the most substantial impact on the model's predictions. This might reflect the critical role of water availability in agricultural success.

4.3.2. Classifier Performance Evaluation. Examining Table 3, we observe that the DecisionTreeClassifier, RandomForestClassifier, and GradientBoostingClassifier achieved perfect scores during training across all metrics. However, when considering testing performance, which is indicative of how well a model generalizes to unseen data, the RandomForestClassifier outperforms the others with the highest testing accuracy, precision, recall, and $F1$ score.

The SVC and GaussianNB models also show strong performance, with high values across all testing metrics, indicating robust predictive capabilities and generalization. In contrast, the AdaBoostClassifier demonstrates significant lower scores, suggesting poor fit or potential overfitting during the training phase, leading to poor generalization on the test set.

KNeighborsClassifier and GradientBoostingClassifier exhibit competent testing performance but do not match the RandomForestClassifier's superior balance across all evaluated metrics.

To assess the performance of different classifiers, ROC curves were generated for each model, and the area under the curve (AUC) values were calculated. Figure 5 illustrates the ROC curves, comparing the classifiers based on their true positive rate (sensitivity) and false positive rate. Each curve

Table 3: Comparative analysis of classifier performance metrics.

Model	Training accuracy	Testing accuracy	Training precision	Testing precision	Training recall	Testing recall	Training $F1$ score	Testing $F1$ score
SVC	0.990	0.986	0.990	0.986	0.990	0.986	0.990	0.986
Decision tree Classifier	0.997	0.977	0.997	0.977	0.997	0.980	0.997	0.978
Random forest Classifier	0.997	0.993	0.997	0.995	0.997	0.991	0.997	0.993
GaussianNB	0.996	0.990	0.996	0.991	0.996	0.990	0.995	0.990
KNeighbors classifier	0.988	0.977	0.988	0.979	0.988	0.974	0.988	0.975
AdaBoost classifier	0.144	0.104	0.0638	0.060	0.136	0.136	0.073	0.069
Gradient boosting Classifier	0.997	0.979	0.997	0.982	0.997	0.981	0.997	0.980

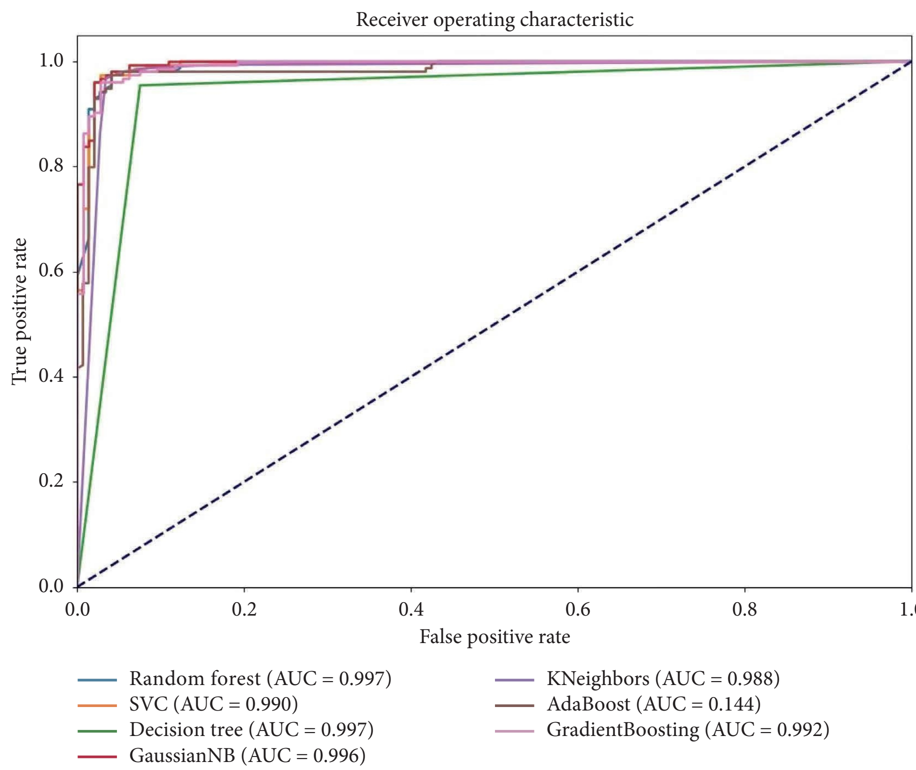

Figure 5: Receiver operating characteristic (ROC) curves for various classifiers.

corresponds to a specific classifier, with the AUC value reflecting its ability to distinguish between classes. Notably, the RandomForest and DecisionTree classifiers achieved the highest AUC values of 0.997, indicating superior performance.

In conclusion, the RandomForestClassifier emerges as the leading model in this analysis, demonstrating exceptional ability to generalize well from the training data to the testing data, with high marks in accuracy, precision, recall, and $F1$ score.

4.3.3. SHAP Value Analysis. Figure 6 provides a stratified analysis of the mean absolute SHAP values, which quantify the influence of various environmental factors on the predictive model's output for different crop types. Each bar segment, color-coded to represent a specific crop, corresponds to the average magnitude of impact that each environmental factor has on the model's prediction for that crop.

Notably, "humidity" has the broadest range of influence across all crops, suggesting it is a predominant factor in the model's predictions. The variability in the lengths of the "humidity" segment for each crop indicates a differential impact, which may be attributed to the distinct moisture requirements of different crops.

"K" (potassium) also demonstrates a substantial effect on the model's predictions, with particular emphasis on certain crops such as "rice" and "watermelon," highlighting the importance of this nutrient in the growth and yield of these crops. Similarly, "rainfall" shows a significant impact across several crops, aligning with the understanding that water availability is a crucial determinant of agricultural productivity.

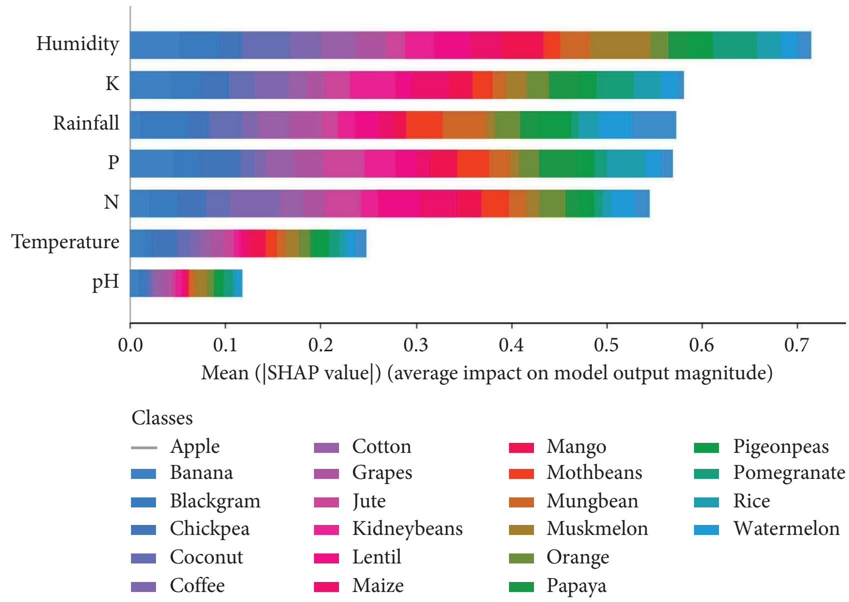

Figure 6: SHAP value analysis of environmental and soil factors affecting crop viability.

Conversely, "pH" levels display a relatively lower mean SHAP values, suggesting a more nuanced role in the model's decision-making process. "Temperature" has a moderate but consistent impact, indicative of its universal relevance to crop viability.

This visualization underscores the varying degrees of importance that specific environmental conditions hold for different crop types within the predictive model. Such insights can guide targeted agricultural practices and resource allocation by emphasizing the environmental factors most critical for each crop's successful cultivation. The analysis also reinforces the value of explainable AI in providing transparency and actionable intelligence in agricultural decision-making systems.

The SHAP summary plots provided depict the impact of different features on the model's output for various crop classes. The SHAP summary plots for the classes "Apple" and "Banana" shown in Figures 7 and 8 reveal the features influencing the model's predictions. In both plots, features such as nitrogen (N), phosphorus (P), potassium (K), rainfall, humidity, temperature, and pH are depicted with SHAP values, indicating their impact on the model's output. For "Apple," we observe a prominent influence of phosphorus (P) and potassium (K), with high positive SHAP values suggesting a strong positive effect on the model's prediction of this class. In contrast, the "Banana" class shows nitrogen (N) with the highest positive SHAP values, implying it is a significant positive driver for predicting the Banana class. Comparing the two, it is evident that while some features are influential for both classes, their impact varies. For instance, rainfall appears to have a mixed influence with both positive and negative SHAP values for "Banana," whereas it is more uniformly negative for "Apple." This suggests that the model predicts "Apple" less frequently in conditions of higher rainfall. For instance, in regions with higher rainfall, the model might favor recommending "Banana" over "Apple," and in nutrient-rich soils, "Apple" might be favored given the positive correlation with P and K.

In summary, the integration of SHAP into our predictive modeling framework has significantly augmented the interpretability of crop recommendations. SHAP values facilitate a deeper understanding of the predictive model by quantifying the contribution of each feature to the prediction. This allows for a granular analysis of how different environmental factors such as soil composition, weather conditions, and crop characteristics influence crop viability assessments.

4.3.4. LIME Interpretability Analysis. The local explanation plots for the classes "Banana" and "Apple," derived from LIME analysis shown in Figures 9 and 10 provide nuanced insights into the model's predictions. For "Banana," the plot indicates that low pH and rainfall, along with high humidity, temperature, and particularly potassium levels ($K > -0.00$), contribute positively to the prediction of this class. This suggests that bananas thrive in conditions with adequate humidity and temperature, aligning with their tropical nature, while excessive rainfall and acidic soils are less ideal.

Conversely, the "Apple" class plot emphasizes the positive influence of higher phosphorus ($P > 0.42$) and moderate nitrogen levels ($N > -0.47$), alongside a preferred lower temperature range ($-0.00 < \text{temperature} \leq 0.58$). These factors are characteristic of the temperate climates where apples typically grow well. Interestingly, both classes show a negative impact from rainfall, indicating that the model may associate excessive rainfall with lower suitability for these crops.

Comparing the two, while potassium has a pronounced positive impact on banana predictions, it appears neutral for apples. Conversely, phosphorus is a significant positive driver for apples but not for bananas. This distinction reflects the different soil nutrient requirements of these crops.

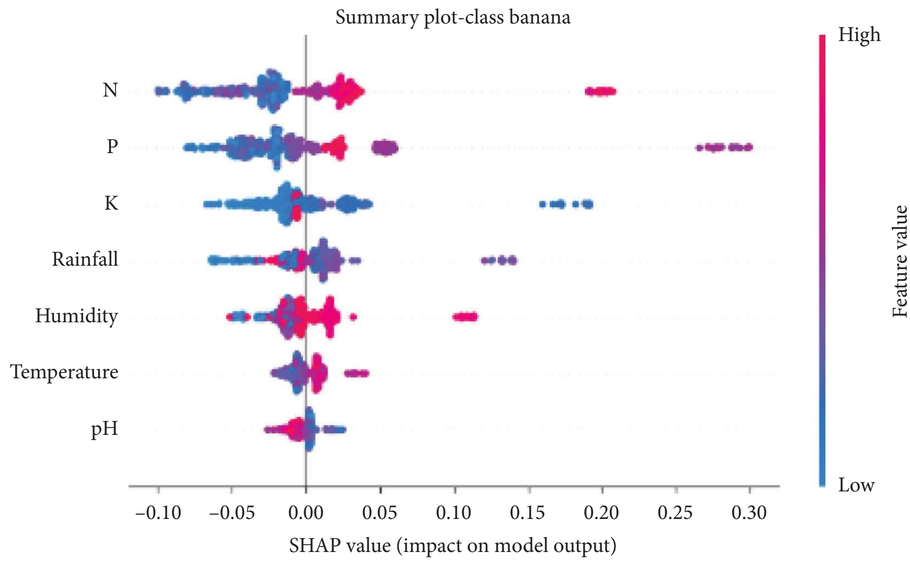

Figure 7: SHAP summary of predictors for apple cultivation.

Figure 8: SHAP summary of predictors for banana cultivation.

Figures 11 and 12 display two LIME for machine learning model predictions, one for the class "Banana" and another for "Apple." LIME helps to explain the predictions of any classifier in an interpretable and faithful manner by approximating it locally with an interpretable model.

For the class "Banana," the model is highly confident about its prediction, as indicated by a probability of 1.00. High phosphorus ($P > 0.44$) levels are the most significant positive contributor to this classification, which could suggest that this nutrient is vital for bananas. Conversely, a lower pH level ($\text{pH} \leq -0.65$) negatively influences the prediction, implying that acidic conditions are less favorable for bananas.

In the case of "Apple," the prediction is also made with full certainty (probability of 1.00). Here, humidity (> 0.83) and higher phosphorus levels ($P > 0.44$) are the main positive drivers, while lower temperature ($\text{temperature} \leq -0.56$) and pH ($\text{pH} \leq -0.65$) are negative influencers. This might indicate that apples thrive in conditions with adequate moisture and nutrient levels but are less likely to be recommended in cooler, more acidic soils.

Comparing the two, phosphorus consistently appears as a significant positive factor for both fruits, highlighting its importance in the cultivation of these crops. However, the pH level negatively affects both, suggesting neither crop prefers highly acidic soils. Notably, temperature has opposing effects: It is a negative contributor for apples but not a strong factor for bananas, which might indicate a preference for warmer growing conditions for bananas. The model's reliance on these features reflects the real-world agricultural knowledge that both bananas and apples require specific environmental conditions to thrive.

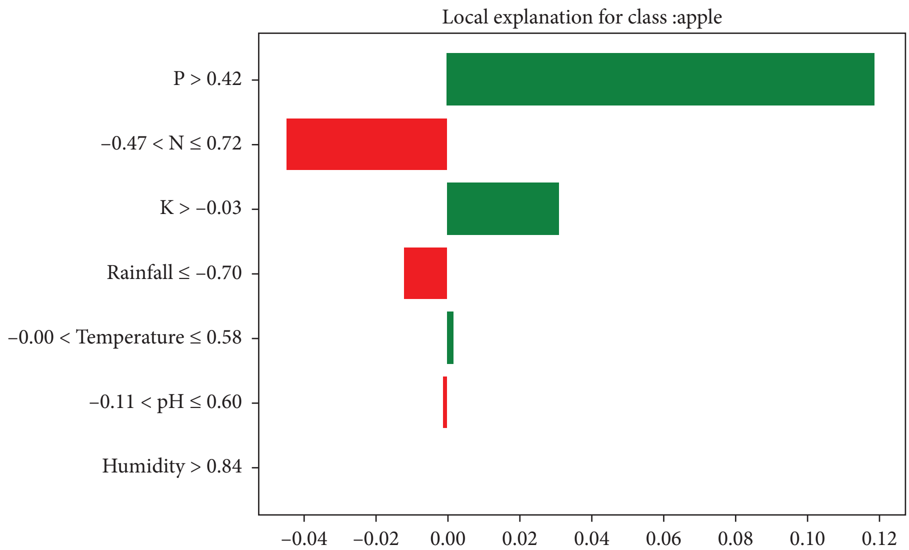

Figure 9: Local analysis of key factors influencing apple cultivation.

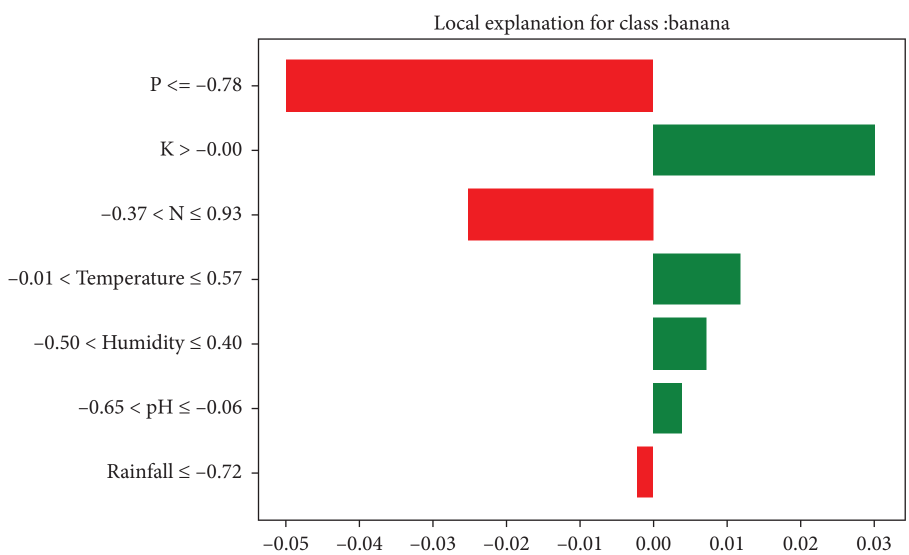

Figure 10: Local analysis of key factors influencing banana cultivation.

In summary, integrating local interpretability with LIME has dramatically influenced our proposed explanatory predictive model for crop recommendation. LIME enhances the model's interpretability, validation, and user acceptance by providing transparent, intuitive, and localized explanations. Understanding and validating individual crop recommendations empowers farmers to make data-driven decisions, ultimately leading to improved agricultural productivity and sustainability. The influence of LIME on our model and results highlights the significance of interpretability in AI systems, especially in domains such as agriculture, where transparency and trust are paramount.

5. Discussion

The results obtained from our proposed explanatory predictive model for crop recommendation, which combines RF, Shapley values, and LIME, provide valuable insights into the significance of interpretability in agricultural decision-making. In this section, we discuss the implications of our findings, the advantages of the model, and its potential impact on agriculture.

5.1. Significance and Practical Implications. The primary advantage of our model lies in its ability to balance accuracy with interpretability, a crucial feature for practical agricultural applications. The high predictive accuracy of RandomForestClassifier ensures reliable crop recommendations, while the integration of SHAP values and LIME explanations provides a transparent and interpretable model. This transparency is critical for building trust among farmers and agricultural stakeholders, who may be hesitant to rely on black-box machine learning models without understanding the underlying decision-making process.

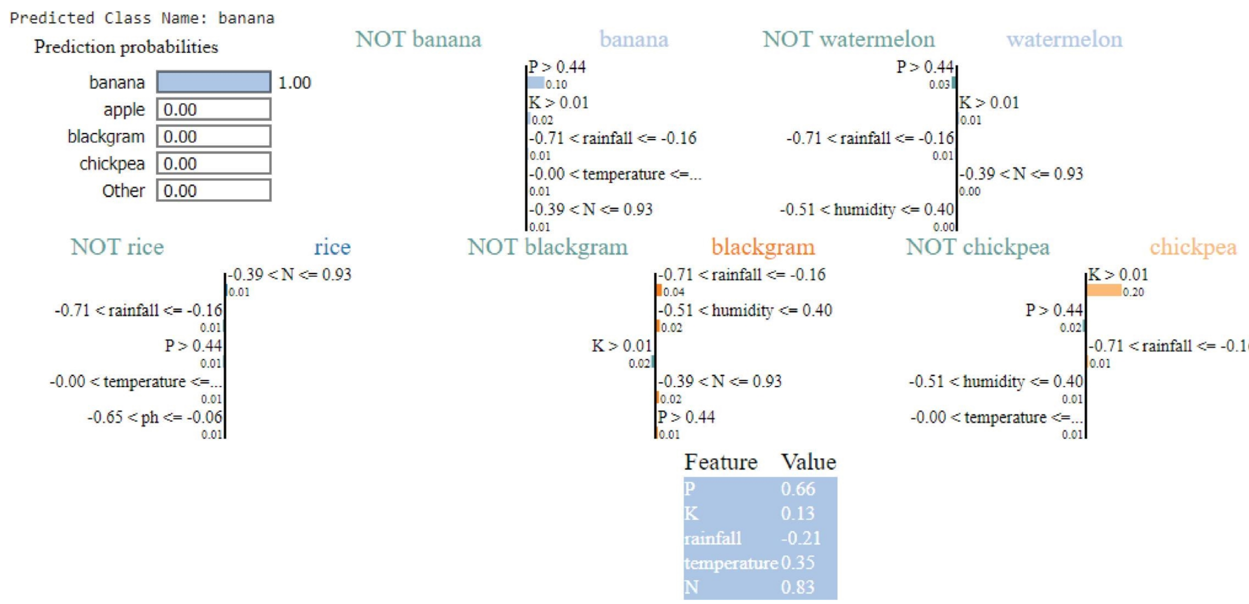

Figure 11: LIME explainer output for predictive analysis of banana crop classification.

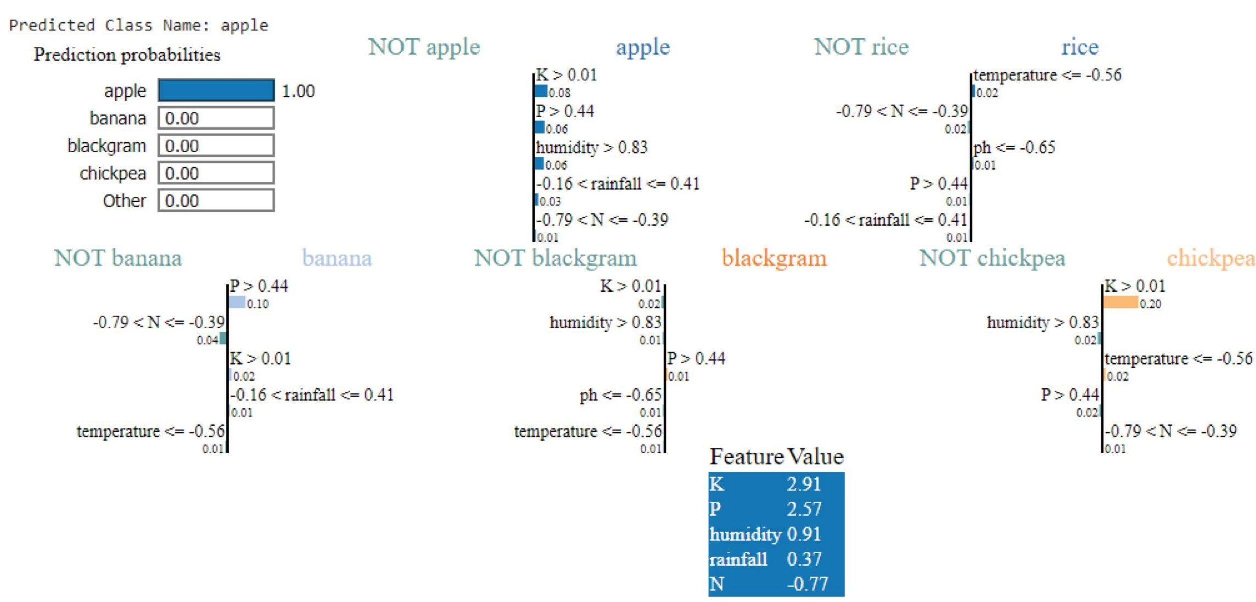

Figure 12: LIME explainer output for predictive analysis of apple crop classification.

5.2. Practical Implications of Results. The practical implications of our findings are significant. Farmers can leverage the model's insights to make informed decisions about crop selection based on specific environmental and soil conditions. For example, the high importance of "rainfall" and "humidity" as identified by SHAP values suggests that water management practices should be prioritized. Understanding the role of nutrients such as phosphorus and potassium can guide fertilization strategies to optimize crop yield and quality. In addition, the localized insights provided by LIME explanations can help farmers understand the suitability of different crops for their specific conditions. For instance, the preference of "banana" for high potassium and low pH environments and "apple" for moderate temperatures and high phosphorus, can inform planting decisions and soil management practices tailored to these crops' needs.

5.3. Comparison With Existing Studies. Our findings are consistent with the existing agricultural research, which emphasizes the importance of environmental factors such as rainfall, humidity, and soil nutrients in crop viability. Studies have shown that adequate rainfall and soil nutrients are critical for crop growth and yield. The insights provided by SHAP and LIME further validate these findings, offering a quantifiable measure of the impact of these factors on crop predictions.

5.4. Enhancing Trust and Acceptance. The interpretability of our model is a significant advantage in enhancing trust and acceptance among users. By providing transparent explanations for crop recommendations, farmers can understand the reasoning behind the model's decisions, making them more likely to adopt and rely on the technology. This transparency also allows for the identification of potential biases or limitations in the model, ensuring that the recommendations are fair and reliable.

5.5. Generalizability and Scalability. Our model's ability to generalize well to unseen data makes it applicable to a wide range of agricultural regions and environmental conditions. This scalability allows for the adaptation of the model to larger datasets and multiple crops, making it a versatile tool for diverse agricultural settings.

5.6. Ethical Considerations. From an ethical standpoint, incorporating interpretability in AI models is crucial. Transparent crop recommendations enable users to identify potential biases or limitations in the model's decision-making process, mitigating risks of erroneous recommendations due to biased training data or model assumptions.

5.7. Limitations and Future Directions. Despite its advantages, our model has limitations. The interpretability achieved through SHAP values and LIME explanations may not be equally accessible to all users. Future research should focus on developing more user-friendly visualizations and interfaces to effectively present the model's insights to nontechnical stakeholders.

In summary, our proposed explanatory predictive model for crop recommendation is a valuable tool in modern agriculture, aligning predictive accuracy with interpretability. By combining machine learning, SHAP values, and LIME, we provide transparent insights into the crop selection process, enabling farmers to make well-informed decisions. The model's trustworthiness and potential for enhancing agricultural productivity make it a significant contribution to AI in agriculture. As the agricultural sector embraces the benefits of interpretable AI, our research underscores the importance of adopting ethical and transparent AI models to drive sustainable development and food security.

6. Conclusion

In this study, we developed a predictive model for crop recommendation that enhances transparency and interpretability using advanced machine learning techniques. By integrating the RF algorithm with Shapley values and LIME, we addressed significant challenges found in traditional crop recommendation systems. Our model exhibited high accuracy in predicting suitable crops, as validated through extensive experiments and analysis. Utilizing Shapley values, we identified the impact of critical factors such as nitrogen, phosphorus, potassium, soil pH, rainfall, and humidity, providing farmers with valuable insights for informed decision-making.

The transparency and justifiability of our model's recommendations are crucial for building trust and acceptance among farmers and agricultural stakeholders. By enabling the identification of potential biases and limitations, our approach underscores the ethical considerations in employing AI for crop recommendations. This research significantly contributes to agricultural decision-making by introducing a robust and interpretable crop recommendation model. It bridges the gap between complex machine learning models and the necessity for understandable explanations, offering a practical tool for optimizing crop selection and promoting sustainable farming practices. Our work aligns with global efforts to achieve food security, efficient resource use, and sustainable agricultural development.

Despite the considerable promise shown by our model, there are areas that warrant further research and improvement. Future work should focus on developing more intuitive and user-friendly interfaces to make the model's insights accessible to a broader range of users, including nontechnical stakeholders. Incorporating a wider range of climatic variables could enhance the model's accuracy and applicability. In addition, applying the model to different geographic regions will help ensure its effectiveness across diverse agricultural contexts. Conducting long-term studies will be essential to evaluate the model's impact on agricultural productivity and sustainability over time.

In conclusion, our study sets the stage for the future integration of interpretable AI in agriculture. By providing farmers with clear and transparent insights, we aim to support global initiatives for food security, resource efficiency, and sustainable development. We anticipate that ongoing advancements in this field will bring transformative benefits to agriculture and beyond.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Conflicts of Interest

The authors declare no conflicts of interest.

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