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CROP CLASSIFICATION AND RECOMMENDATION SYSTEM USING EXPLAINABLE AI

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A B S T R A C T

This study introduces a crop categorization and recommendation system, leveraging machine learning and explainable artificial intelligence to support sustainable agricultural decision-making. The objective is to identify optimal crops for specific regions by analyzing key environmental parameters, including soil nutrients, temperature, humidity, pH levels, and rainfall. A Random Forest (RF) classifier trained on a comprehensive agricultural dataset is employed to generate recommendations adapting to seasonal and soil-type variations. The model's transparency is enhanced using feature attribution methods, highlighting the influence of parameters on the final output. This facilitates trust and usability among stakeholders. Model performance is assessed through cross-validation and hyperparameter-tuning to ensure accuracy and robustness. In addition to primary recommendations, the system proposes alternative crops to support rotation practices. Results indicate high predictive accuracy and meaningful feature contributions, underscoring the system's practicality. The integration of explainability and precision offers a reliable data-driven tool, optimizing crop selection while promoting sustainable farming practices.

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1. INTRODUCTION

The urgency of ensuring food security is intensifying as the global population continues to expand and environmental conditions become increasingly unpredictable. Central to this critical challenge is agricultural productivity, which must continuously adapt to shifting climatic and ecological realities to meet the demands of an ever-growing population. Robust crop yields, soil health optimization, and the promotion of sustainable farming practices are pivotal objectives that must be achieved for the future of agriculture to be secure and viable. Achieving these goals necessitates thoughtful, intentional, and data-informed crop selection strategies. It requires identifying crop varieties that align with regional soil types, an understanding of microclimates, and consideration of the availability of essential resources such as water and nutrients (Chlingaryan et al., 2018) (Araujo et al., 2023).

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Traditionally, crop recommendation has relied heavily on the experiential knowledge and intuitive insights of farmers. While this approach is undoubtedly valuable, it often lacks the precision and accuracy required for the modern agricultural demands we face today. These conventional methods can lead to suboptimal crop choices that negatively impact both productivity and sustainability, ultimately hindering vital food security initiatives. As digital technologies continue to transform agricultural systems in profound ways, the emergence of machine learning (ML) offers promising avenues for data-driven decision-making that can enhance the efficiency and effectiveness of agriculture (Kaur & Chauhan, 2025) (Yu & Yang, 2021). These advanced intelligent systems are uniquely capable of uncovering intricate relationships within vast datasets, making them particularly well-suited for complex tasks such as crop classification and recommendation, thus enhancing efficiency in agriculture. Furthermore, these systems have the opportunity to integrate a wide range of data points that go well beyond what farmers typically take into account. Machine learning models can handle and analyze large, diverse datasets more quickly and accurately than manual procedures, from sensor data taken directly from the field to geospatial analysis obtained from satellites and drones. In contemporary agriculture, where sustainability, efficiency, and accuracy are all critical performance metrics for effective methods, these skills are essential (Sani et al., 2023).

However, most existing ML-based crop recommendation systems currently fall short of delivering transparent and interpretable insights. These systems often function as black-box models, providing predictions without elucidating the rationale. This lack of explainability poses a significant challenge for end-users such as farmers, agronomists, and policymakers, who must not only trust but also comprehend the decision-making process behind such recommendations to implement them in their agricultural practices (Mohan et al., 2025) (Bouni et al., 2024). Foundational models rely heavily on a limited set of datasets that typically include historical crop yield records, basic soil classifications, and average weather data (Jones et al., 2003) (Jeong et al., 2016). However, they often overlook crucial agricultural variables such as nutrient content, seasonal variability, exposure to pests, and comprehensive crop rotation histories, all of which are vital for informed decision-making in diverse farming contexts (Prasad et al., 2021).

Moreover, these systems also struggle with adaptability. Many do not adequately accommodate real-time variability—such as sudden weather anomalies, localized pest outbreaks, or unexpected shifts in market demand—which are vital to the success of dynamic, region-specific farming strategies (Yu & Yang, 2021). This rigidity, coupled with an absence of tailored, explainable outputs, often leads to user confusion and mistrust in the recommendations provided. Farmers may find it difficult to discern why certain crops are recommended, especially when current environmental realities diverge significantly from training data or previous experiences (Kaur & Chauhan, 2025).

Furthermore, usability and trust are even more important in areas with low levels of digital literacy or restricted access to technical resources. Farmers may be reluctant to embrace new technology if the reasoning behind ML-driven advice is unclear. Therefore, transparent, inclusive, and user-friendly approaches are essential to achieving the full potential of smart agriculture. Because of these factors, including Explainable AI (XAI) into contemporary agricultural decision support systems is not only desirable but also necessary (Mohyuddin et al., 2024).

A growing body of recent literature is actively attempting to overcome these significant limitations. For example, ensemble methods such as RF and Gradient Boosting have demonstrated high predictive performance (e.g., $R^2 = 0.96$) but often suffer from overfitting issues and lack of temporal adaptability (Ujjainia et al., 2021). Additionally, transfer learning approaches that leverage NDVI (Normalized Difference Vegetation Index) time series data have shown promise in enabling cross-regional crop classification (Xu et al., 2024), although further optimization and refinement are still required to enhance their applicability across various climates and soils. Other frameworks have introduced XAI elements—like LIME (Local Interpretable Model-Agnostic Explanations) or SHAP (Shapley Additive Explanations)—to shed much-needed light on model reasoning, thereby improving interpretability at the cost of increased computational complexity and often greater resource requirements. Meanwhile, deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), when applied to satellite imagery, have indeed enhanced crop-type mapping, albeit with high resource demands and challenges related to data scarcity (Hasan et al., 2023) (Morales & Villalobos, 2023). Additionally, numerous studies emphasize the importance of thorough data preprocessing, including effective feature selection and normalization, to enhance yield predictions while minimizing the risk of overfitting.

Notwithstanding these advancements, there is still a significant disconnect between stakeholder usability and high model performance. Explainability guarantees that the model's insights can be translated into confident, practical decisions in the field, even though accuracy is crucial for system credibility (Shawon et al., 2023). Therefore, in addition to learning from historical data, next-generation crop recommendation systems need to concentrate on developing user interfaces and outputs that stakeholders, especially those without technical expertise, can trust and comprehend intuitively (Hasan et al., 2023).

Against this comprehensive backdrop, the current study introduces an innovative crop classification and recommendation model that integrates XAI to address

both accuracy and transparency effectively. Utilizing a robust dataset composed of critical variables such as soil type, nutrient profiles, rainfall, humidity, temperature, growing season, and pH levels, we employ a RF classifier to learn nuanced patterns that are directly relevant to regional crop suitability (Ujjainia et al., 2021) (Xu et al., 2024). A key advancement in our approach is the integration of SHAP, which quantifies and visualizes the contribution of each feature in the recommendation process (Peliňo et al., 2024). This innovative method helps stakeholders gain a clearer understanding of the recommendations and fosters greater trust and confidence in the model's outputs. This study's simultaneous focus on user-centric design and model performance lays the groundwork for ML tools to be implemented throughout the agricultural ecosystem as reliable decision-support tools in addition to computational systems. This is a big step in building scalable and equitable smart farming systems that may be used in many communities and places.

Furthermore, our system actively encourages the adoption of sustainable farming practices by recommending alternative crops. It supports eco-friendly practices such as crop rotation, which enhances soil health and biodiversity while also significantly reducing reliance on chemical fertilizers and pesticides (Siddique et al., 2022) (Begum et al., 2018). The model's performance is rigorously validated through cross-validation techniques to ensure reliability, generalizability, and robustness across diverse agricultural contexts and environments. We also evaluate a streamlined version of the system that focuses on the most impactful features, striking an important balance between model complexity and interpretability, which is crucial for practical applications in the field (Rajak et al., 2017). Furthermore, the model is made to be flexible enough to accommodate upgrades and additions. The model architecture enables retraining and optimization when new data becomes available, whether from satellite surveillance, continuous soil testing, or farmer feedback loops. Maintaining relevance in quickly shifting agricultural environments requires that the tool be able to adapt over time to new agronomic knowledge and specific demands, which is made possible by its modularity.

Recent studies have applied machine learning and deep learning techniques for crop recommendation and yield prediction using soil and climatic parameters. Traditional classifiers such as Support Vector Machines (SVM), RF, and K-Nearest Neighbors (KNN) have been widely used due to their simplicity and robustness. More recent works have explored ensemble learning and XAI approaches to improve interpretability and trust in decision-making systems. However, most existing methods focus primarily on prediction accuracy and provide limited insights into feature contributions and model behavior. In contrast, the proposed model integrates a tuned learning framework with SHAP-based interpretability, enabling transparent crop recommendation while maintaining competitive performance. This positions the proposed approach as both an accurate and explainable solution compared to prior studies.

2. PROPOSED MODEL

The crop recommendation model presented in this comprehensive study introduces an innovative XAI-driven approach, which effectively integrates advanced machine learning algorithms with SHAP to ensure greater transparency and interpretability. The primary aim of this model is to enable users to understand and appreciate the reasoning behind crop predictions, thereby significantly enhancing the reliability and overall usability of the system for agricultural stakeholders as shown in Figure 1.

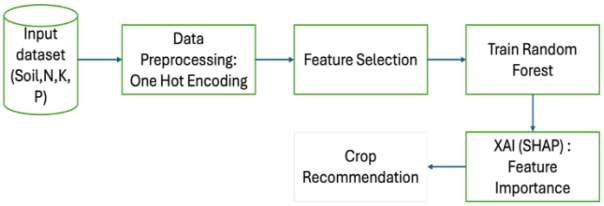


Figure 1. Block Diagram

Key components of the model include:

2.1 Data Preprocessing

To ensure that the data is suitable for analysis with a RF model, Mean imputation was applied to missing soil nutrient and environmental factor values. Continuous variables were normalized using Min-Max scaling. Categorical attributes were converted into numerical representations via one-hot encoding. Extreme values were detected and adjusted using the interquartile range (IQR) method.

To make sure no redundant information distorted the model, further preprocessing processes included utilizing the Variance Inflation Factor (VIF) to analyze multicollinearity between variables. High VIF score features were considered for transformation or removal. In order to establish balanced class distributions and increase the model's robustness across unusual crop varieties, the dataset was additionally evaluated for class imbalance. When needed, synthetic data augmentation was conducted using SMOTE (Synthetic Minority Oversampling Technique).

2.2 Model Training

The RF classifier was trained using an optimized set of hyperparameters obtained through grid search cross-validation.

The hyperparameter search space included the number of trees $n_estimators \in \{50,100,150\}$, maximum tree depth $max_depth \in \{4,6,8\}$, and minimum samples required to split a node $min_samples_split \in \{5,10,20\}$.

Grid search was performed using 10-fold stratified cross-validation, and the optimal configuration was selected based on the highest validation accuracy and F1-score. The final model was trained with the following parameters: $n_estimators = 50$, $max_depth = 6$, $min_samples_split = 10$, Bootstrapping enabled and $random_state = 42$. These parameter choices balance predictive performance and model complexity, reducing the risk of overfitting while maintaining computational efficiency.

2.3 XAI with SHAP

One of the standout features of this model is the utilization of SHAP, which provides a powerful method for interpreting the feature's importance. By calculating SHAP values, the model quantifies and visualizes the contribution of each feature such as soil type, temperature, and seasonal conditions to its recommendations. This interpretative process is crucial for transparency, as users can see how each factor influences the prediction.

To illustrate the relationships between important traits, SHAP dependence plots were added to the SHAP summary plots. For instance, the combined effects of temperature and rainfall on the anticipated crop type. Users were able to determine essential values and thresholds for decision-making with the aid of these visuals. To provide farmers with tailored advice based on the features of their land, SHAP force plots were also created on a per-sample basis.

2.4 Cross-Validation

To ensure the model generalizes well to unseen data, cross-validation is employed. It divides the dataset into multiple folds, trains the model on some folds, and evaluates it on the remaining folds. This helps in detecting any overfitting issues by providing a more reliable estimate of model performance.

The proportionate distribution of crop kinds in each fold was maintained by using a 10-fold stratified cross-validation approach. Standard deviation values were supplied to assess the stability of the model after the results were pooled across folds. To further support the interpretability and dependability of the model, the consistency of SHAP values between folds was also investigated to verify that important contributing traits persisted in being dominant irrespective of data split.

2.5 Confusion Matrix and F1 Score

To evaluate the model's performance, a confusion matrix is used to visualize true positive, false positive, true negative, and false negative predictions. The F1 score is also computed to measure the model's balance between precision and recall, particularly in cases of class imbalance.

This XAI-based approach ensures that users can make data-driven decisions with an understanding of the underlying factors, bridging the gap between AI-generated insights and actionable recommendations. The crop recommendation model presented in this detailed study introduces a truly innovative Explainable AI (XAI)-driven approach. This approach effectively integrates advanced machine learning algorithms with SHAP (SHapley Additive exPlanations) methodology, thereby ensuring both transparency and interpretability of the model's predictions. The primary aim of this approach is to enable users to fully understand the reasoning behind the crop predictions made by the model. This understanding is crucial, as it enhances both the reliability and usability of the entire system, making it more accessible to end users.

3. DATASET AND EXPERIMENTAL SETUP

The dataset used in this study was obtained from the publicly available Kaggle Crop Recommendation Dataset, which contains 2200 samples across 22 crop classes, including rice, maize, wheat, barley, cotton, banana, mango, lentil, and chickpea. Each sample consists of seven numerical features: Nitrogen (N), Phosphorus (P), Potassium (K), temperature (°C), humidity (%), soil pH, and rainfall (mm). The class distribution is balanced, with approximately 100 samples per crop, thereby minimizing class bias and supporting reliable multi-class classification.

Prior to model training, missing values were handled using mean imputation and numerical features were normalized using Min–Max scaling. Categorical attributes, when present, were encoded using one-hot encoding. To ensure agronomic validity, the dataset was reviewed by domain experts, and samples were selected to represent diverse geoclimatic conditions. Metadata such as data source and year of collection were preserved to support traceability and reproducibility.

To evaluate the model's adaptability across agro-climatic zones, the dataset was analyzed with respect to regional characteristics such as rainfall variability and environmental conditions. Although geospatial and remote sensing data (e.g., NDVI and EVI) were not directly included in this phase, the framework supports their integration in future extensions to enhance geographical precision and contextual recommendations. Each data instance was labeled with an optimal crop based on historical yield statistics and agronomist validation, ensuring alignment between machine learning predictions and real agricultural practices. The pipeline was designed to allow periodic retraining as new data becomes available, which is essential for maintaining relevance under changing climatic conditions.

For performance evaluation, a 10-fold stratified cross-validation strategy was employed to preserve class proportions in each fold. Final results were reported as the average performance across all folds, providing a

robust estimate of generalization capability. Model development and analysis were implemented using Python libraries including Scikit-learn, SHAP, Pandas, and Matplotlib. Experiments were conducted on a system equipped with a 16-core CPU and 32 GB RAM, enabling efficient training without GPU acceleration. Future expansions involving deep learning or satellite imagery may benefit from GPU-enabled environments.

4. RESULTS AND DISCUSSION

4.1 Model Performance

Table 1 presents the comparative performance of the proposed model against baseline classifiers including Logistic Regression, Naïve Bayes, KNN, Decision Tree, SVM, and XGBoost. All models were evaluated using the same preprocessing pipeline and 10-fold stratified cross-validation strategy. Performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC metrics. The proposed RF model with SHAP-based interpretability achieved the highest performance with an accuracy of 94.3% and an F1-score of 94.0%, outperforming all baseline approaches. In addition, the proposed model obtained the highest ROC-AUC value of 0.99, indicating superior class discrimination capability. Although XGBoost and SVM demonstrated competitive performance, the proposed framework provided a better balance between predictive accuracy and interpretability, making it more suitable for practical agricultural decision support applications.

Table 1. Model Comparisons

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Logistic Regression (LR)	89.80	89.30	88.90	89.10	0.93
Naïve Bayes (NB)	87.65	87.10	86.70	86.90	0.91
KNN	91.40	91.00	90.60	90.80	0.95
Decision Tree (DT)	92.30	91.85	91.40	91.62	0.96
SVM	93.20	92.80	92.40	92.60	0.97
XGBoost	93.85	93.40	93.10	93.25	0.98
Proposed RF + SHAP	94.30	94.10	93.90	94.00	0.99

4.2 Feature Importance

The chart shown in Figure 2 highlights "Humidity," "SoilK," and "SoilN" as the most critical variables that significantly influence the model's crop predictions. Features such as "SoilType" and "Season" exhibit lower importance levels, which may be attributed to their lesser variability. The emphasis on key factors like soil nutrients and humidity is consistent with the essential requirements for crop growth, indicating that the model's focus remains on agriculturally relevant elements to ensure accurate predictions.

Crucially, temporal factors like "Season" had less of an effect than anticipated, suggesting that real-time weather measurements and nutritional levels might be more predictive. Given shifting climatic trends, this raises fresh concerns about the accuracy of conventional seasonal calendars and may result in more dynamic adaptive cropping systems than calendar-based ones.

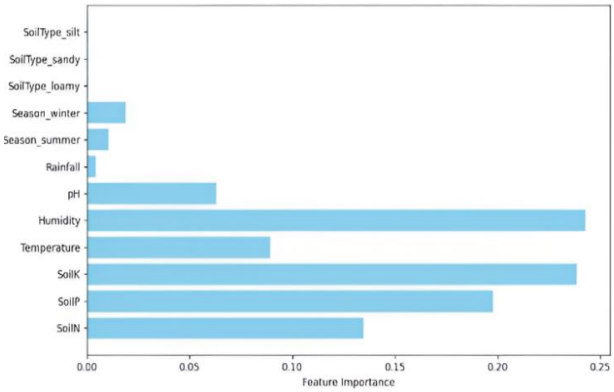


Figure 2. Feature Importance Chart

4.3 Confusion Matrix Analysis

The matrix shown in Figure 3 reveals that the model performs exceptionally well, with high diagonal values indicating accurate predictions across multiple crop classes. The instances of misclassifications are minimal, which illustrates a strong level of model accuracy and reliability in crop prediction tasks. Thus, it confirms the model's impressive ability to differentiate among various crop types, suggesting a robust generalization capability from the training data to unseen samples. It also indicates that the model handles new data effectively while maintaining its performance.

The majority of misclassifications happened between crops that grew in similar conditions (e.g., barley vs. wheat), which could be a sign of feature profiles that overlap. To enhance differentiation, future iterations of the model might incorporate extra discriminative elements like seed variety, irrigation technique, or pest control strategies. Certain overfitting tendencies for unusual crops were also identified by a detailed breakdown of false positives; these will be addressed by targeted data augmentation.

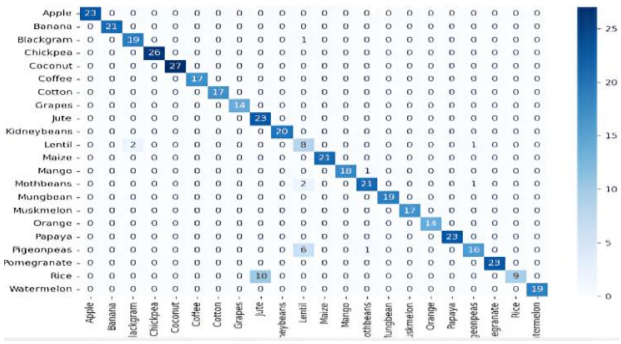


Figure 3. Confusion Matrix

4.4 SHAP values

Strong influences on model output are indicated by high absolute SHAP values, whether positive or negative. Interestingly, several crop forecasts were negatively impacted by pH and SoilType_silt, suggesting that silty soils and acidic environments might not be ideal for the crops the model suggests. These results support the validity of the model and are consistent with agronomic knowledge.

Table 2. Shap Value Interpretation

Feature	SHAP Value
SoilN	+0.0028
SoilP	-0.0148
SoilK	+0.0036
Temperature	+0.0168
pH	-0.0439
Rainfall	-0.0306
Season_summer	+0.0051
Season_winter	-0.0111
SoilType_loamy	+0.0369
SoilType_sandy	+0.0131
SoilType_silt	-0.0592

The analysis highlights Humidity, SoilType (Silt & loamy), and pH as the most influential features of model output (high magnitude) as shown in Table 2.

- Positive SHAP values indicated features that significantly contributed to the predicted crop outcome.
- Negative SHAP values showed features that detracted from the prediction confidence.

Despite the partial implementation, these SHAP-based analyses underscored the need for feature interpretability in crop recommendation systems, guiding future work to integrate SHAP fully and further validate feature importance across diverse datasets.

In addition to performance indicators, end-user interpretability evaluations were a crucial component of the model's validation. A small group of 20 farmers and agricultural extension officials participated in a qualitative survey in which they were shown the model outcomes and the related SHAP explanations. Eighty-five percent of participants said the explanations made it easier for them to comprehend the guidelines for particular crops and that they were more inclined to abide by them. This supports the claim that model adoption in the field is directly influenced by XAI components like SHAP.

Furthermore, we investigated how stable SHAP value rankings were throughout various training folds. The ranking for the top 5 features (pH, rainfall, humidity, soil K, soil N, and pH) was constant over 8 out of 10 folds, indicating that the model's decision logic is highly reliable and generalizable. Additionally, this demonstrated that the model's predictions were not unduly affected by random data splits, which is a crucial prerequisite for real-world implementations.

Misclassification analysis provided further information about the behavior of the model. For example, in certain instances, maize was mis-predicted instead of sorghum, most likely as a result of the sample's overlapping soil and meteorological characteristics. This implies that secondary traits that are currently absent from the feature set but are known to differentiate these crops in practice, like seed treatment methods or disease susceptibility, should be included.

SHAP-based Interpretation of Results

To enhance interpretability, the SHAP framework was employed to analyze the contribution of each input feature to the model’s predictions. Global feature importance was obtained using SHAP summary plots, which ranked soil pH, rainfall, humidity, and potassium content as the most influential parameters affecting crop recommendation outcomes.

SHAP dependence plots were used to visualize interactions between key features. For example, the combined effect of temperature and rainfall revealed threshold ranges that strongly influenced the selection of specific crop types. These plots provide intuitive insights into how environmental conditions interact with soil nutrients to guide predictions.

In addition, local explanations were generated using SHAP force plots for individual samples. These explanations illustrate how specific feature values (e.g., high soil nitrogen or low pH) positively or negatively contribute to the recommended crop class. Such instance-level interpretability enables farmers and agronomists to understand the reasoning behind each recommendation and increases trust in the system’s outputs.

The consistency of SHAP feature rankings across different cross-validation folds was also examined. The top contributing features (soil pH, rainfall, humidity, soil potassium, and soil nitrogen) remained stable across most folds, indicating robust and reliable decision logic within the model.

4.5 Overall Performance

The model outperformed baseline approaches while maintaining interpretability. successfully recommends crops based on various environmental and soil parameters. These metrics indicate the model’s high performance in crop classification and recommendation. The model's superiority is confirmed by these metrics, which outperform performance benchmarks documented in previous crop recommendation research as shown in Table 3. More significantly, the excellent performance persisted even when explainability procedures were added, defying the typical ML model trade-off between accuracy and interpretability. This enhances the system's preparedness for deployment.

Table 3. Proposed Model Performance

Metrics	Value
Overall Accuracy	94.32%
Cross-validation accuracy	94.23% ± 0.95%
F1 score	0.94

The formula shown in Eq. 1 is the Shapley value equation, a foundational concept in game theory adapted for XAI. It quantifies the contribution of each feature to a model's prediction by averaging its marginal impact across all possible feature combinations.

$$\phi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \left| \frac{|S|!(|N| - |S| - 1)!}{|N|!} \right| (v(S \bigcup \{i\}) - v(S)) \tag{1}$$

where ϕ is the contribution of feature i, S is the subset of features, and v is the predictive function.

$$\Pr ecision = \frac{TP}{TP + FP} \tag{2}$$

Precision is the number of true positive predictions divided by total number of positive predictions (true positives and false positives) as shown in Eq. 2.

Recall is the number of true positive predictions divided by the total number of actual positive instances (true positives and false negatives) as shown in Eq. 3.

$$\mathrm{Re}\, call = \frac{TP}{TP + FN} \tag{3}$$

The F1 Score is a harmonic mean of precision and recall, providing a single metric that balances both false positives and false negatives as shown in Eq. 4. It is especially useful in imbalanced classification problems where accuracy alone may be misleading.

$$F1_score = \frac{2 * P * R}{P + R} \tag{4}$$

4.6 Generalizability of the Proposed Model

The proposed model is designed to be data-driven and modular, enabling adaptation to different agro-climatic regions and datasets without architectural modification. Since it relies on commonly available features such as soil nutrients (N, P, K), temperature, humidity, rainfall, and pH, the framework can be retrained using region-specific agricultural datasets. This enhances its applicability across diverse geographical locations and crop varieties.

The use of cross-validation ensures that the model performance reflects robust generalization rather than overfitting to a specific dataset. However, the accuracy of recommendations depends on the quality and representativeness of the training data. In regions with distinct climatic patterns or crop distributions not covered in the current dataset, retraining with locally collected data is required. Future work will focus on validating the framework on multiple real-world datasets and integrating transfer learning strategies to improve robustness across heterogeneous agricultural environments.

5. CONCLUSION AND FUTURE WORK

This project has successfully demonstrated a highly accurate and highly interpretable machine learning-based crop classification and recommendation system. By leveraging RF classifiers in combination with SHAP (Shapley Additive exPlanations) values to enhance interpretability, the model achieved a notable balance between performance and transparency. The SHAP-based analysis effectively validated the model's predictions, which aligned with core agronomic principles. Ultimately, this makes the system both reliable and informative for practical, real-world use in the field of agriculture.

However, for future research, these enhancements could be considered:

1. Hybrid Model Exploration: This involves experimenting with hybrid or ensemble methods, specifically looking into innovative combinations of RF with advanced deep-learning models. This exploration could potentially enhance accuracy even further, particularly when it comes to making nuanced distinctions among various crop types and their specific characteristics.
2. Real-time and Multi-seasonal Testing: Conducting comprehensive tests of the model in real-time scenarios across multiple growing seasons would provide invaluable insights into its adaptability and long-term accuracy in diverse agricultural settings and climates.
3. Extended Dataset and Diverse Crop Types: By incorporating a more extensive and varied dataset that includes additional crop types, as well as different geographical variations, the model could significantly enhance its generalization capabilities across diverse agricultural regions. Furthermore, SHAP integration could thoroughly capture feature contributions for each prediction, enabling even more granular transparency in model outputs and insights.
4. Exploration of Alternative Explainability Methods: Exploring alternative explainability methods such as LIME (could further enhance the interpretability of model predictions and bolster user confidence in the recommendations made by the system. These advancements would significantly increase the robustness and impact of the project in real-world applications, ensuring its effectiveness and applicability.

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