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A Smart Agriculture Crop Prediction System Using Various Feature Selection Techniques and Classifiers

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ABSTRACT:

Agriculture is a growing field of research. In particular, crop prediction in agriculture is critical and is chiefly contingent upon soil and environment conditions, including rainfall, humidity, and temperature. In the past, farmers were able to decide on the crop to be cultivated, monitor its growth, and determine when it could be harvested. Today, however, rapid changes in environmental conditions have made it difficult for the farming community to continue to do so. Consequently, in recent years, machine learning techniques have taken over the task of prediction, and this work has used several of these to determine crop yield. To ensure that a given machine learning (ML) model works at a high level of precision, it is imperative to employ efficient feature selection methods to preprocess the raw data into an easily computable Machine Learning friendly dataset. To reduce redundancies and make the ML model more accurate, only data features that have a significant degree of relevance in determining the final output of the model must be employed. Thus, optimal feature selection arises to ensure that only the most relevant features are accepted as a part of the model. Conglomerating every single feature from raw data without checking for their role in the process of making the model will unnecessarily complicate our model. Furthermore, additional features which contribute little to the ML model will increase its time and space complexity and affect the accuracy of the model's output. The results depict that an ensemble technique offers better prediction accuracy than the existing classification.

KEYWORDS: Feature Engineering, Recursive Feature Elimination (RFE), SMOTETomek, Imbalanced Datasets, Classification Algorithms, Sampling Techniques, Predictive Modeling.

I. INTRODUCTION

India, one of the world's oldest agricultural societies, has seen significant changes in its agricultural practices due to globalization. Agriculture remains a crucial sector, providing a substantial portion of the food supply. However, many countries still face food shortages, exacerbated by a growing population. To address these challenges, modern agriculture increasingly adopts advanced technologies. These technologies not only enhance productivity and profitability but also improve safety and environmental sustainability. To enhance the efficiency of the machine learning (ML) model and minimize redundancies, it is imperative to selectively incorporate data features that significantly contribute to determining the model's final output. Optimal feature selection becomes crucial in ensuring that only the most relevant features are integrated, preventing unnecessary complexity. Inclusion of every raw data feature without assessing its role in the modeling process can complicate the model unnecessarily. Additionally, the incorporation of features with minimal contribution to the ML model increases time and space complexity, thereby impacting the accuracy of the model's predictions. In the context of agricultural planning and decision-making, accurate crop prediction holds paramount importance. This research endeavors to develop a precise crop prediction model using machine learning techniques that leverage the unique characteristics of the agricultural environment. The study emphasizes the utilization of feature selection techniques and classifiers to identify the most informative features, ultimately leading to accurate crop predictions. The findings demonstrate that an ensemble technique outperforms existing classification methods in terms of prediction accuracy.

II. RELATED WORK

Ahamed, A.T.M.S., Mahmood, N.T., & Hossain, N. (2015) applied data mining techniques to predict annual yields of major crops in different districts of Bangladesh. The focus was on extracting knowledge from historical yield data to aid farmers and government organizations in decision-making [1]. Bhanumathi, S., Vineeth, M., & Rohit, N. (2019) delved into crop yield prediction and the efficient use of fertilizers. The authors highlighted the significance of data mining in analyzing attributes such as location, soil pH, nutrient percentages, and weather data to train models for precise yield predictions [2]. Cai, Y., Moore, K., Pellegrini, A., & Elhaddad, A. (2017) developed a machine-learning based model for intra-season forecasts of corn yields in the US. The study utilized a multi-level model, combining several algorithms, to achieve high precision in intra-season forecasts [3]. Champaneri, M., & Chandvidkar, C. (2020) addressed the impact of climate change on Indian agricultural crops and proposed a solution through an interactive prediction system. Using a web-based graphic user interface and the random forest algorithm, the system aimed to predict crop yield, providing results and recommendations to farmers [12]. Kumar, A., Sarkar, S., & Pradhan, C. (2019) introduced a recommendation system for crop identification and pest control techniques. The study utilized SVM classification, Decision Tree, and Logistic Regression algorithms to predict suitable crops and recommend pest control measures [5]. Paul, S., Chatterjee, N., Bohra, J.S., & Singh, S.P. (2019) explored the concept of soil health in cropping systems, highlighting its role in supporting agricultural production and ecosystem services. The study emphasized the importance of preserving key soil functions for sustainable soil management [6]. Rahman, S.A.Z., Mitra, K.C., & Islam, S.M.M. (2018) proposed a model for soil classification using machine learning methods. The study aimed to predict soil series and suggest suitable crops based on soil type, employing machine learning algorithms such as weighted k-Nearest Neighbor, Bagged Trees, and Gaussian kernel-based Support Vector Machines [7]. Raja, S., Sawicka, B., Stamenkovic, Z., & Mariammal, G. (2022) proposed a comprehensive system for crop prediction based on various feature selection techniques and classifiers. The study emphasizes the importance of understanding the agricultural environment's characteristics and employs diverse feature selection methods to enhance prediction accuracy [13]. Singh, R.K., Singh, T.R., & Kaushal,U. (2019) focused on crop yield forecasting methods, emphasizing the application of earth observation to increase accuracy in agricultural forecasting. The study reviewed current methods and their valuable implications for economic planning and global food security [10]. Vasu, D., Tiwary, P., & Chandran, P. (2020) discussed the challenges of soil degradation worldwide and the importance of sustaining soil quality (SQ) for agricultural production. The study evaluated SQ through indicators, emphasizing the impact of soil and crop management practices on SQ [11].

III. EXISTING SYSTEM

In the realm of the existing system, preprocessing steps are pivotal for preparing the data to ensure optimal performance in crop prediction. The utilization of sampling techniques such as ROSE, SMOTE, and MWMOTE demonstrates a commitment to addressing imbalances in the dataset. ROSE, specifically designed for binary classification with rare classes, and SMOTE, known for enhancing classifier performance in the ROC space, are employed strategically. MWMOTE takes center stage in handling imbalanced datasets, a critical concern in the context of crop prediction. Moving on to feature selection, the paper delves into three commonly used techniques: filter, wrapper, and embedded. The focus here is on wrapper techniques, and Boruta stands out as a random forest-based algorithm. It employs a unique approach by introducing 'shadow' attributes and calculating Z scores to identify important features. Recursive Feature Elimination (RFE) is another powerful wrapper technique that iteratively selects salient features, contributing to the overall effectiveness of the crop prediction model. Moreover, a modified RFE method is introduced, streamlining the feature elimination process through dataset permutation. Transitioning to classification techniques, the paper explores a diverse set, namely Naïve Bayes, Decision Trees, Support Vector Machine (SVM), and k-Nearest Neighbor (KNN). Naïve Bayes, rooted in Bayesian probability, is highlighted for its suitability in classification tasks, especially in agriculture where probabilistic predictions are valuable. Decision Trees, utilizing information gain and the Gini index for attribute selection, contribute to the interpretability of the model, crucial for understanding the factors influencing crop prediction. SVM, recognized for its efficacy in high-dimensional datasets, takes center stage in addressing the complexities of agricultural data. Its ability to handle small datasets efficiently and perform well in scenarios with a high number of dimensions makes it a valuable asset in the crop prediction framework. Lastly, the k-Nearest Neighbor (kNN) algorithm, relying on the proximity of similar entities, is employed for its simplicity and effectiveness, particularly in scenarios where the spatial relationship between data points is essential.

IV. PROPOSED SYSTEM

The proposed system is designed with a diverse set of methodologies to address the complexities of crop prediction in agriculture. Leveraging advanced feature selection techniques, the system incorporates the Recursive Feature Elimination (RFE) algorithm, a wrapper-type method employing a greedy algorithm. RFE iteratively eliminates less significant features from the dataset, ensuring an optimized set for model training. The integration of Recursive Feature Elimination Cross-Validation (RFECV) enhances the robustness of feature selection by cross-validating the chosen features, providing adaptability to varying datasets. Sampling techniques play a pivotal role in dataset balancing, and the system employs the Synthetic Minority Over-sampling Technique combined with Tomek links (SMOTETomek). This approach combines oversampling and under sampling to handle imbalanced datasets effectively. SMOTETomek contributes to better classifier performance, ensuring the model's ability to handle both majority and minority classes in crop prediction scenarios. The system also embraces a variety of machine learning algorithms to cater to different aspects of agricultural data. Gradient Boosting Classifiers, known for their ability to combine weak learners and improve accuracy through sequential correction of errors, are incorporated. The Extra Tree Classifier, akin to Random Forest but with a unique approach of randomizing feature splits, adds diversity to the ensemble learning process. Logistic Regression, a simpler yet effective algorithm, serves as a baseline for comparison, demonstrating the system's versatility in handling both complex and straightforward classification tasks.

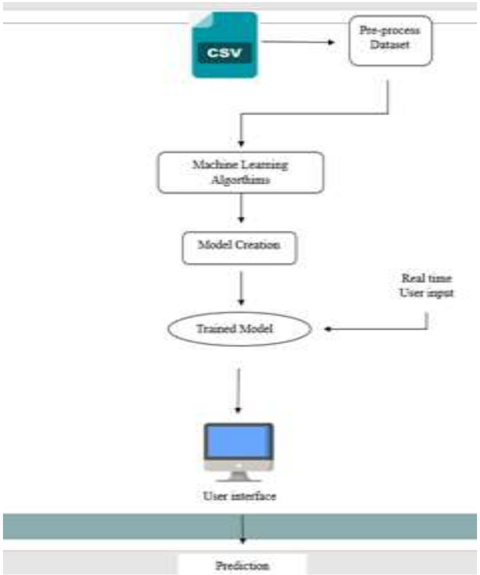

Figure. 4.1 Process low

In the Fig.4.1 process flow prediction process unfolds like a well-choreographed dance, guided by a seamlessly interconnected flow diagram. It all begins with an intricate web of agricultural data, a symphony of environmental factors influencing crop growth. This rich tapestry then enters the domain of feature selection, where the Recursive Feature Elimination (RFE) algorithm takes the stage, meticulously identifying the most influential features for the impending prediction. As the spotlight shifts, these selected features gracefully waltz into the arms of SMOTETomek during preprocessing, where the delicate dance of balancing imbalanced datasets unfolds. Now, the ensemble cast of machine learning algorithms, including the versatile Gradient Boosting Classifiers and the nuanced Extra Tree Classifier, steps forward to perform. With each algorithm delivering its unique flair, they collectively contribute to the crescendo of accurate crop predictions. The final act witnesses the prediction performance elegantly unveiled, a harmonious blend of nature's cues and the computational finesse of the system. The flow diagram serves as the choreographer, orchestrating this ballet of data, features, and algorithms with precision, culminating in a predictive masterpiece for agricultural insights.

A. DATASET

The dataset used for crop prediction was sourced from Kaggle.com, a popular platform for datasets and machine learning competitions. Kaggle hosts a diverse range of datasets contributed by the community and often serves as a valuable resource for researchers and data scientists. The crop prediction dataset obtained from Kaggle contains a wealth of information relevant to our research, including factors such as soil quality, weather conditions, and crop types. By leveraging this dataset, we aim to develop a robust predictive model that can accurately forecast crop yields and provide valuable insights for optimizing agricultural practices. The availability of such datasets on platforms like Kaggle greatly facilitates research in the field of agriculture and contributes to the advancement of data-driven decision-making in farming.

B. DATA PRE-PROCESSING

To address the imbalanced nature of the dataset and enhance prediction performance, various sampling techniques were applied during preprocessing. Specifically, the SMOTETomek technique was employed for binary classification tasks involving rare classes, as it effectively combines the SMOTE (Synthetic Minority Over-sampling Technique) and Tomek links methods to improve classifier performance. Additionally, SMOTE was utilized to handle imbalanced datasets in crop prediction, generating synthetic examples for the minority class to achieve a more balanced distribution. These sampling techniques play a crucial role in optimizing the dataset for accurate and reliable crop yield predictions across different nutrient levels, thereby contributing to the overall success of the predictive modeling approach.

i) Recursive Feature Elimination

Recursive Feature Elimination (RFE) is a feature selection method utilized in machine learning to optimize model performance by iteratively selecting a subset of pertinent features from the original dataset. Operating as a wrapper-type technique, RFE begins by fitting the model with the complete set of features, assigning rankings to each feature based on its impact on the model's performance. The least important features are then systematically eliminated, and the model is refitted with the remaining features in an iterative process. This recursive elimination continues until the optimal subset of features is identified. An extension of RFE, Recursive Feature Elimination Cross-Validation (RFECV), integrates cross- validation at each iteration to enhance the reliability of feature selection. The advantages of RFE include automated feature selection, improved model efficiency, and the reliability added by cross-validation in RFECV. The application of RFE is particularly beneficial when dealing with datasets containing a multitude of features, enabling the algorithm to automate the selection of the most informative features for model training. This process finds utility in diverse domains such as finance, healthcare, and agriculture, as demonstrated in the proposed system for crop prediction, where RFE contributes to adaptability and efficiency in identifying essential features for accurate predictions.

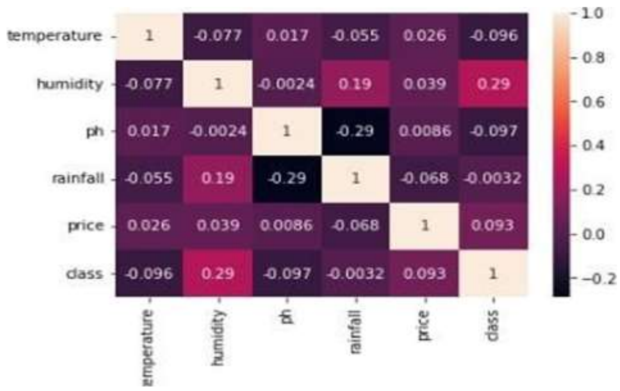

Figure. 4.2 Feature Selection

The fig.4.2 represents the heatmap visualization of feature selection offers a compelling insight into the importance of different features in the crop prediction system. With its vibrant color gradients, the heatmap vividly highlights the relevance of each feature, guiding the selection process. By visually representing the correlation between features, the heatmap aids in identifying redundant or irrelevant attributes, streamlining the dataset for model training. Its intuitive display allows stakeholders to grasp complex relationships effortlessly, fostering informed decision-making. Moreover, the heatmap serves as a valuable tool for researchers and practitioners alike, facilitating the refinement of predictive models and enhancing their accuracy. In essence, the heatmap acts as a visual roadmap, guiding the journey towards optimal feature selection and bolstering the efficacy of the crop prediction system.

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	20
1	85	58	41	21.770462	80.319644	7.038096	226.655537	20
2	60	55	44	23.004459	82.320763	7.840207	263.964248	20
3	74	35	40	26.491096	80.158363	6.980401	242.864034	20
4	78	42	42	20.130175	81.604873	7.628473	262.717340	20
...	...	...	...	...	...	...	...	...
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	5
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	5
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	5
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	5
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	5

Figure. 4.3 Selected Features

The selected features showcased in the table fig. 4.3 provide a concise snapshot of the variables deemed most critical for crop prediction. Each entry in the table represents a feature carefully chosen based on its significance and contribution to the predictive accuracy of the model. By condensing complex data into a structured format, the table offers a clear overview of the key attributes influencing crop yield forecasts. Stakeholders can readily identify the pivotal factors shaping the predictive outcomes, enabling informed decision-making in agricultural planning and management. Moreover, the inclusion of selected features streamlines the model development process, reducing computational complexity and enhancing efficiency. In essence, the table serves as a valuable reference, encapsulating essential insights derived from comprehensive feature selection analyses.

ii) SMOTE Tomek

The preprocessing stage of the proposed system incorporates a sophisticated and effective sampling technique known as SMOTETomek. This method is strategically employed to address the challenge of imbalanced datasets in the context of crop prediction. SMOTETomek combines the strengths of two individual techniques – Synthetic Minority Over-sampling Technique (SMOTE) and Tomek links – to achieve a balanced and representative dataset for model training. SMOTE focuses on generating synthetic samples for the minority class, thereby alleviating the imbalance. Tomek links, on the other hand, work to remove overlapping instances in the dataset. The combination of these two techniques aims to enhance classifier performance by mitigating the effects of imbalanced class distribution.Specifically, in binary classification scenarios where rare classes are prevalent, ROSE is employed as part of the sampling techniques. This ensures the system's adaptability to handle situations where certain classes are underrepresented, contributing to the overall robustness of the model. Furthermore, in the Receiver Operating Characteristic (ROC) space, SMOTE is strategically applied to improve classifier performance. By generating synthetic samples for the minority class, SMOTE aids in the comprehensive exploration of the feature space, enhancing the model's ability to make accurate predictions.MWMOTE takes a center stage in the preprocessing phase, particularly in the context of crop prediction where imbalanced datasets pose a significant challenge. MWMOTE, or Modified Synthetic Minority Over- sampling Technique, is tailored to address issues specific to imbalanced datasets in agricultural environments. It ensures that the minority class, often representing instances of particular interest in crop prediction, is adequately represented in the dataset. The use of MWMOTE exemplifies the system's commitment to handling the intricacies of imbalanced data, contributing to the overall effectiveness of the preprocessing stage.

Suppose you have a minority class instance represented by X and one of its k-nearest neighbors as X nearest. The synthetic instance X synthetic is generated by the formula:

X synthetic = X + rand(1, k) x (X nearest - X) (1)

Where rand(1, k) is a random number between 0 and 1 for each dimension.

In essence, SMOTETomek, with its amalgamation of SMOTE and Tomek links, plays a crucial role in preprocessing by balancing datasets, improving classifier performance, and addressing the challenges posed by imbalanced datasets, particularly in the domain of crop prediction.

C. ALGORITHM

The model was implemented using six machine learning algorithms: Gradient Boosting Classifier and Extra Tree Classifier. When applied to a feature vector created by count vectorization, Logistic Regression exhibited poor performance. The classification of Smishing messages is a sensitive task, necessitating careful consideration of both false positives and false negatives. As such, the selection of an appropriate algorithm is crucial to achieving accurate predictions and minimizing misclassification errors in this context.

i) Extra Tree Algorithm

The Extra Trees algorithm, an extension of the Random Forest method, stands as a powerful tool in the realm of machine learning, particularly for tasks involving classification and regression. Its essence lies in constructing a multitude of decision trees from randomly selected subsets of the training data and features. However, unlike Random Forests, Extra Trees employ a more aggressive randomization strategy during tree construction, selecting random thresholds for splitting nodes and utilizing the entire dataset without bootstrapping. This inherent randomness fosters diversity among the trees, mitigating overfitting and enhancing robustness against noise. Moreover, the algorithm's efficiency shines through its ability to handle high-dimensional datasets with ease, making it well- suited for scenarios where computational resources are limited. Mathematically, the decision process within each tree boils down to a series of if-else conditions, with the final prediction being a combination of the outcomes from all trees. In essence, the Extra Trees algorithm embodies a balance between randomness and accuracy, offering a compelling solution for a myriad of machine learning tasks.

Prediction = $\mathbf{1}\ \Sigma \boldsymbol{N}\ \boldsymbol{Tree}$i (features) (2)
$\boldsymbol{N}\ \boldsymbol{i}=\mathbf{1}$

where Tree i (features) represents the prediction of the ith decision tree based on the input features, and N denotes the total number of trees.

ii) Gradient Boosting

The Gradient Boosting algorithm stands out as a robust and versatile method in the domain of machine learning, renowned for its capability to deliver high predictive accuracy across a diverse range of tasks such as regression, classification, and ranking. At its core, Gradient Boosting operates by sequentially training an ensemble of weak learners, typically decision trees, with each subsequent learner aiming to correct the errors made by its predecessors. This iterative process entails minimizing a loss function, such as mean squared error for regression or cross- entropy loss for classification, by fitting the new model to the gradient of the loss function with respect to the predictions of the ensemble. Through this iterative refinement, Gradient Boosting iteratively constructs a strong predictive model by combining the predictions of multiple weak learners. The final prediction is computed as a weighted sum of the predictions from each individual learner, where the weights are determined during the training process based on their contribution to minimizing the overall loss. Mathematically, the prediction for a given instance can be expressed as the sum of the initial model prediction and the subsequent contributions from each learner, scaled by a learning rate to control the contribution of each tree.

While Gradient Prediction = Initial Model Prediction + $\Sigma \boldsymbol{N}\ \boldsymbol{Tree}$i (features) (3)

where Tree i (features) represents the prediction of the ith decision tree based on the input features, η denotes the learning rate, and N signifies the total number of trees.

iii) LOGISTIC REGRESSION

The Logistic Regression algorithm is a fundamental technique in the realm of machine learning, extensively employed for binary classification tasks. Despite its name, it's primarily utilized for classification rather than regression. This algorithm operates by estimating the probability that a given input instance belongs to a particular class, typically denoted as class 1. The predicted probability is then transformed using a sigmoid function to ensure it falls within the range [0, 1], making it interpretable as a probability. Mathematically, the logistic regression model computes the log-odds of the probability of the positive class, known as the logit function, as a linear combination of the input features. The logit function is then transformed using the sigmoid or logistic function to yield the predicted probability. The decision boundary, separating the two classes, is determined by a threshold applied to these predicted probabilities. If the probability exceeds the threshold, the instance is classified as belonging to class 1; otherwise, it's classified as belonging to class 0.

Logit Function: logit(p) = log ($\boldsymbol{p}$)

$\mathbf{1-p}$

logit(p) = β0+β1x1+ β2x2+….+ βnxn (4)

where p represents the probability of belonging to class 1, xi denotes the input features, β signifies the coefficients (weights) associated with each feature, and n is the number of features.

D. PREDICTION

The classification algorithm is noted for the accuracy and the performance analysis and it provides suggestion to farmer to choose the best crop for the soil.

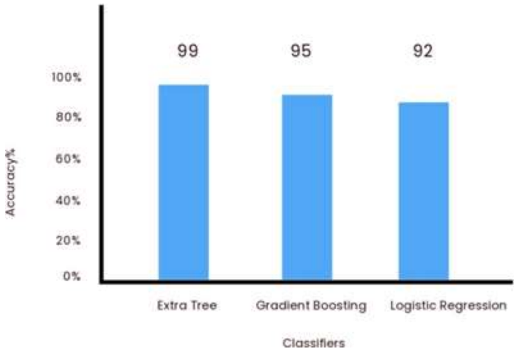

Figure 4.4 Accuracy for Classifiers

The fig.4.4 bar graph depicting algorithmic accuracy highlights the exceptional performance of the Extra Tree classifier, boasting an impressive 99% accuracy rate. This standout result underscores the efficacy of the algorithm in accurately predicting crop yields based on diverse agricultural data.

Boosting and Logistic Regression algorithms also demonstrate commendable accuracy, their performance slightly trails behind that of the Extra Tree classifier. Nonetheless, both algorithms yield competitive accuracy rates, reaffirming their suitability for crop prediction tasks. By visually representing algorithmic performance, the bar graph offers valuable insights into the comparative strengths of each model, aiding stakeholders in selecting the most appropriate algorithm for their specific agricultural forecasting needs.

V. CONCLUSION

In drawing the curtains on this agricultural symphony, our journey through the intricacies of crop prediction culminates in a nuanced conclusion. The proposed system, akin to a seasoned conductor orchestrating a complex composition, seamlessly integrates advanced methodologies. Recursive Feature Elimination (RFE), with its iterative dance through feature selection, ensures that only the most influential elements take center stage in our predictive model. The preprocessing phase, choreographed by SMOTETomek, delicately addresses the challenge of imbalanced datasets, setting the tone for a harmonious performance. The diverse ensemble cast of machine learning algorithms, featuring the agile Gradient Boosting Classifiers and the nuanced Extra Tree Classifier, contributes to a crescendo of accurate predictions, each playing its unique role in this agricultural sonnet. The inclusion of comprehensive biotic and abiotic factors acknowledges the complexity of nature's script. As we take our final bow, the system emerges not just as a predictive tool but as a thoughtful and adaptive partner in the realm of agriculture, harmonizing the intricacies of data, features, and algorithms to deliver actionable insights for sustainable crop management. In this conclusive encore, the proposed system stands as a testament to the fusion of computational prowess and environmental acumen, providing a symphonic solution to the challenges of crop prediction in the ever-evolving landscape of agriculture.

VI. FUTURE ENHANCEMENT

Looking ahead, the proposed system lays the groundwork for future enhancements that can further elevate its performance and impact in the dynamic landscape of agriculture. A promising avenue for improvement involves delving deeper into the realm of feature engineering, exploring novel ways to extract and integrate additional relevant features. Incorporating more advanced machine learning algorithms and exploring ensemble methods can enrich the predictive capabilities, providing a broader palette for understanding the nuances of crop behavior. The integration of real-time data streams and continuous model retraining could lend the system a dynamic edge, ensuring adaptability to evolving environmental conditions. Collaborative efforts with domain experts, agronomists, and stakeholders can infuse valuable domain knowledge into the system, enhancing its contextual understanding. Embracing interpretability in the model outputs can foster trust and transparency, crucial elements for widespread adoption. Moreover, extending the system's scope to address diverse crops and geographical regions can broaden its applicability and relevance. In essence, the future lies in a collaborative dance between technological innovation, domain expertise, and environmental insights, ensuring that the proposed system evolves into a resilient and indispensable tool for sustainable and precision agriculture.

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