Journal of Information Technology and Digital World (ISSN: 2582-418X)
www.irojournals.com/itdw/

AgroSage: A GA-Tuned Random Forest Framework for Smart Disease Diagnosis and Fertilizer Recommendation in Vegetable Crops

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Abstract

Precision agriculture requires scalable, interpretable, and deployable solutions ensuring consistent delivery of crop health assessments and nutrient management guidance. In this work, a two-stage plant disease classification and fertilizer recommendation system for tomato, potato, and pepper plants is proposed and named AgroSage, utilizing a GA-tuned Random Forest (RF) model. Unlike deep learning methods, which are computationally expensive and demand a large amount of data, AgroSage makes use of hand-engineered features such as color histograms, Local Binary Patterns (LBP), and shape descriptors derived from leaf images to build an efficient and interpretable classifier. The system is designed to detect five common diseases: early blight, late blight, bacterial wilt, anthracnose, and leaf curl virus. After a disease is detected, a second GA-optimized random forest-based model takes the crop type and soil macronutrient (N, P, K) levels as input to recommend the type and quantity of fertilizer that should be applied and the application method. Both models are incorporated into a lightweight web interface that allows for real-time inference and multilingual input, as well as offline caching. Stratified cross-validation verifies classification accuracy over 95% and fertilizer application accuracy at 95.2%. Customized forms of AgroSage can provide site-specific, disease-specific, and soil-specific recommendations to help farmers achieve healthy and sustainable crop yields, reduce chemical overuse, and bolster the resilience of precision agriculture systems in resource-constrained farming areas.

DOI: https://doi.org/10.36548/jitdw.2025.2.007
Received: 28.04.2025. received in revised form: 02.06.2025, accepted: 20.06.2025, published: 04.07.2025

Keywords: Random Forest, Genetic Algorithm, PlantVillage, Fertilizer Recommendation, Plant Disease Detection, Sustainable Agriculture, Smart Farming, Precision Agriculture, Leaf Feature Extraction, Tomato Potato Pepper.

1. Introduction

Agriculture remains a cornerstone of food security in the world, especially in developing countries. Yet, two serious problems are threatening its sustainability, including the high incidence of plant diseases and the low utilization rate of fertilizers. Pandemic diseases such as early blight, bacterial wilt, anthracnose, and leaf curl virus cause huge losses in high-value crops such as tomatoes, potatoes, and peppers, particularly in low-resource farming communities with little or no diagnostic facilities. At the same time, the uninformed use of fertilizers, partly because of inaccurate soil diagnostics and partly due to the absence of professional guidance, contributes to soil impoverishment, water pollution, and markedly increases production costs [6].

Given these two challenges, there is a requirement for strong, interpretable, and readily accessible decision support tools that can enable farmers to diagnose crop diseases as well as to optimize fertilizer use in a resource-efficient manner [7]. There have been remarkable advances over the past decade in the field of machine learning, which have positively affected agricultural decision support systems. However, there are still a number of deep-learning-based models that are not suitable for deployment in rural settings on account of computation and memory requirements, dependence on large training sets, and lack of interpretability. The necessity of a continuously stable network and the requirement of bulky hardware also make them less feasible to use in the field. The lack of interpretability commonly leads to a lack of trust from the user and a lack of acceptance from non-technical stakeholders. To deal with these issues, we propose AgroSage, a concise and explainable machine learning framework with Genetically Algorithm (GA)-based Random Forest classifiers for two essential tasks: identification of plant diseases alongside the recommendation of proper fertilizer for three economically significant crops (tomato, potato, and pepper). Unlike black-box models, AgroSage utilizes hand-engineered features (color histograms, LBP, and geometric shape descriptors) computed on leaf images to capture visual signs of disease. Such features are light in computation and can adjust to various imaging circumstances, in view of which they are applicable for rural applications.

For the disease classification model, the RF model is optimized with common hyperparameters optimized through GAs (number of trees, depth of the tree, and type of splitting criteria). This evolutionary fine-tuning enhances generalization and prevents overfitting, making it robust to diagnosis despite varying environments [10]. Upon identifying the disease, a second GA-optimized Random Forest model is applied to predict the user site-specific fertilizer recipes (NPK levels) based on detected disease class, crop type, and user-input soil macronutrient contents (N, P, and K). It not only prescribes the type of fertilizer but also recommends the dosage and method of application that enables the farmers to take appropriate action for curative and preventive crop care [3]. To facilitate accessibility and usability, AgroSage is delivered on a mobile/web platform designed with real-time inference, multilingual translation, and offline caching capabilities. The user uploads images of leaves (as much as possible) and the nutrient value of soil, which then sends feedback immediately through an easy-to-use interface even under low-bandwidth conditions [11]. Experimental results are promising: the disease detection module has obtained an accuracy rate of over 95%, and the fertilization recommendation module obtained an accuracy rate of 95.2%. These results validate that the proposed framework of hand-engineered features, Random Forest classifiers, and GA optimization provides high performance at a reasonable complexity, especially for precision farming in limited-resource settings [5].

AgroSage fills the void between machine learning research at the academic level and the tillage field-level agricultural application. Its focus on three key crops and five major diseases, combined with disease-informed nutrient management, supports sustainable farming practices and minimizes input losses, thereby improving crop yield in resource-poor areas [13].

The main contributions of this paper are as follows:

1. We introduce a hybrid AgroSage system with Random Forest models (optimized using GA) for effective disease detection and fertilizer recommendation.
2. The system is designed for three of the most important crops: tomato, potato, pepper, and covers five of the highest impact diseases that apply in field conditions.
3. We present an effective and understandable feature extraction procedure suitable for deployment in low-resource settings.
4. Our models are presented through a user-friendly web application that supports live predictions and multi-language translation.
5. Comprehensive testing reveals high accuracy of both disease and fertilizer modules, which justifies the reliability of the proposed technique.

The organization of the remainder of this paper is as follows. The related works are reviewed in Section 2-column recognition, machine learning in agriculture and nutrient management systems are reviewed. The method, including feature extraction, optimization, and system architecture, is described in Section 3. Experimental results, model evaluation and analysis are shown in Section 4. Section 5 concludes the paper and discusses future work for deployment and practical adoption.

2. Literature Review

Ferentinos (2018) also developed a deep learning model for automatic plant disease diagnosis by using convolutional neural networks to train a model based on a dataset of more than 87,000 leaf images. His research led to classification accuracies of over 99 percent in the lab and showcased the power of deep learning in agriculture. However, this model performed less well when used in the real world due to varying light conditions, background clutter, and unstandardized image quality. The study stressed the importance of dataset quality and environmental control, suggesting that dynamic and lightweight models were necessary for field-level deployment in different farming practices [1]. Mohanty et al. (2016) built a CNN based on the PlantVillage dataset, which was trained to recognize 26 diseases in 14 types of crops. The model performed very well when tested with controlled imaging. The authors mentioned limitations in the use of these models of in field conditions. Disparities in background, lighting, and occlusions in leaf images limited the generalization of the established model. Their work highlights the need for models that are both computationally efficient and robust under the uncontrolled settings of agriculture, where farmers could have access to basic devices and varying imaging conditions [2].

Sladojevic et al. (2016) created an automated disease identification system for plants. This system was trained on leaf shape, texture, and lesion pattern features using a deep neural network. The model successfully diagnosed diseases in real-time with high accuracy and low computational burden. Unlike pure data-driven methods, this approach included interpretable image features that could be deployed in a rural setting. The addition of manually engineered features led to increased performance even with less data. This technique is suitable for agricultural situations that lack technological infrastructure and makes it practical for use by farmers and agricultural officers with little knowledge of how to use the tool [3]. Arogundade et al. (2021) solved soil nutrient optimization using a fuzzy rule-based predictive system. They reasoned about soil test parameters and recommended fertilizer types, which, in contrast to black-box predictions, were interpretable. The fuzzy logic technique assists in handling some of the uncertainties and variabilities in field soil information. This framework proved to be useful for farmers by producing site-specific fertilizer recommendations. However, in the system, the disease status of the plant was not included in the recommendation logic, resulting in relatively limited generalization ability to provide an integrated solution considering both nutrient deficiency and biotic stress contributions [4]. Lavanya et al. (2024) developed an optimization-based fertilizer advisory system based on Gradient Boosted Decision Trees, with Logistic Regression and Genetic Algorithms. Evolutionary tuning was also adopted to discover the ideal hyperparameters, thus enhancing the accuracy and robustness of the classifier. Their research shows that the Genetic Algorithm can increase the adaptability of the crop and soil classifiers used in the machine learning approach. This work underlines the AgroSage framework, where consistent evolutionary optimization is used for RF classifiers in disease diagnosis and fertilizer recommendation. Hybrid learning allows scalability and interpretability, which are particularly important for decision support in agriculture for resource-poor regions [5].

3. System Architecture and Methodology

This section presents the basic method employed in the AgroSage framework to combine machine learning and optimization to diagnose disease and recommend fertilizer. The first step is to extract suitable features from crop leaf images and soil nutrient inputs so that we have a structured dataset that is interpretable. These features are passed to two Random Forest models, which are tuned by a Genetic Algorithm for better performance. The first model identifies crop diseases, and the second offers customized fertilizer advice. In the rest of this section, we present the network architecture, optimization, and dual-model fine-tuning of our proposed method.

3.1 Feature Extraction from Leaf Images and Soil Parameters

In order to fit the rural and resource-constrained setting, AgroSage uses interpretable and lightweight feature extraction for both imagery and tabular inputs. The system initially preprocesses the input leaf images submitted by the user ensure they have similar resolution, scale, and intensity of light. This operation provides consistent structure in the image data and smooths out the noise. Three types of features are computed from images: (i) color histograms that capture variation in pigments associated with chlorosis or necrosis; (ii) Local Binary Patterns (LBP) that describe changes in texture due to fungal or bacterial infection; and (iii) shape features, including contour complexity, aspect ratio, and centroid displacement, that describe the morphological distortion of infected leaves. At the same time as the model input requirement, farmers supply the crop type (tomato, potato, or pepper) and the corresponding soil macronutrient level (N, P, or K). Z-score normalization is performed on these values numerically to address biases caused by their different scales:

$$z = \frac{x - \mu}{\sigma} \qquad (7)$$

Where x is the input value, μ is the feature mean, and σ is the standard deviation [7]. The crop and disease type is encoded as integers or one-hot vectors (e.g., we use 1 for tomato and 0 for early blight). The resulting image-soil feature vector is input to both the disease classification and fertilizer recommendation models. This small, structured input leads to computational efficiency, real-time performance, and excellent classification accuracy across devices. This two-input approach allows AgroSage to work in low-connectivity settings, as shown in Figure 1, with a possible scope of deployment on mobile/web interfaces across rural areas.

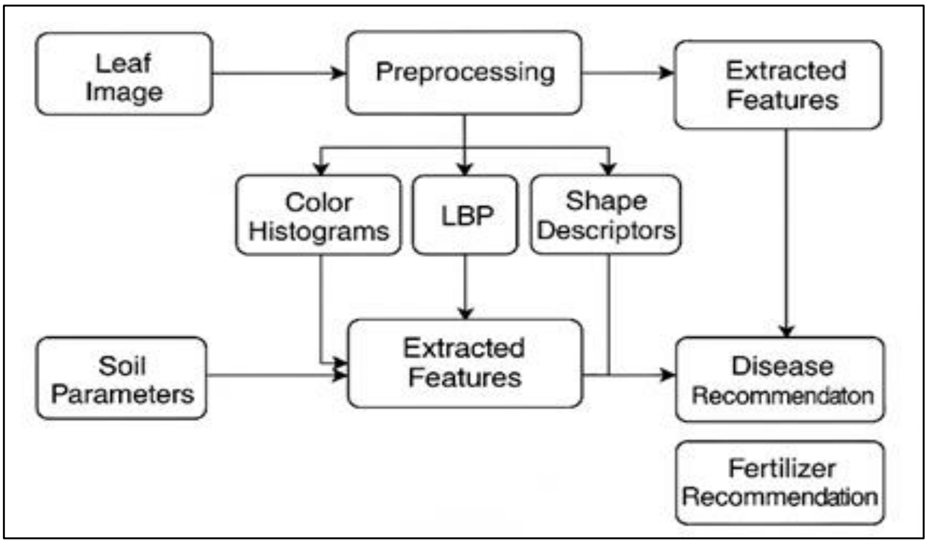

Figure 1. System Architecture of AgroSage Framework

3.2 GA-Optimized Random Forest for Disease Classification

The disease diagnosis model is designed using a Random Forest (RF) classifier that was improved with a Genetic Algorithm (GA) to attain an impressive level of classification accuracy and generalization. The RF model is developed based on the handcrafted features (discussed in Section 3.1) from images to classify five prevalent diseases of crops, namely early blight, late blight, bacterial wilt, anthracnose, and leaf curl virus. To overcome the limitations of static hyperparameter tuning, GA is used to dynamically optimize the number of trees (n_"estimators"), maximum depth (d_"max") and split criterion (Gini or Entropy). The GA optimization process starts with a population of randomly initialized hyperparameter sets, and the hyperparameter sets change with the operations of selection, crossover (probability p_c=0.8), and mutation (p_m=0.05) operations [8]. The model capability of each candidate configuration is measured in terms of five-fold cross-validation accuracy:

$$F(\theta) = 1 - \mathrm{CV}_{\mathrm{error}}(\theta) \qquad (2)$$

Where θ is a set of hyperparameters [2]. All models select the best performing configuration for the final model. The feature importance values on the RF model help us determine which features have a greater impact on disease classification. This enhances transparency and facilitates explainability for nontechnical end-users. The final model is deployed in a real-time web interface in which the user uploads a leaf image and receives an immediate diagnosis. Figure 2 describes the GA optimization procedure to fine-tune the RF model. The disease classifying module consistently achieves an accuracy higher than 95% while retaining model interpretability and execution speed.

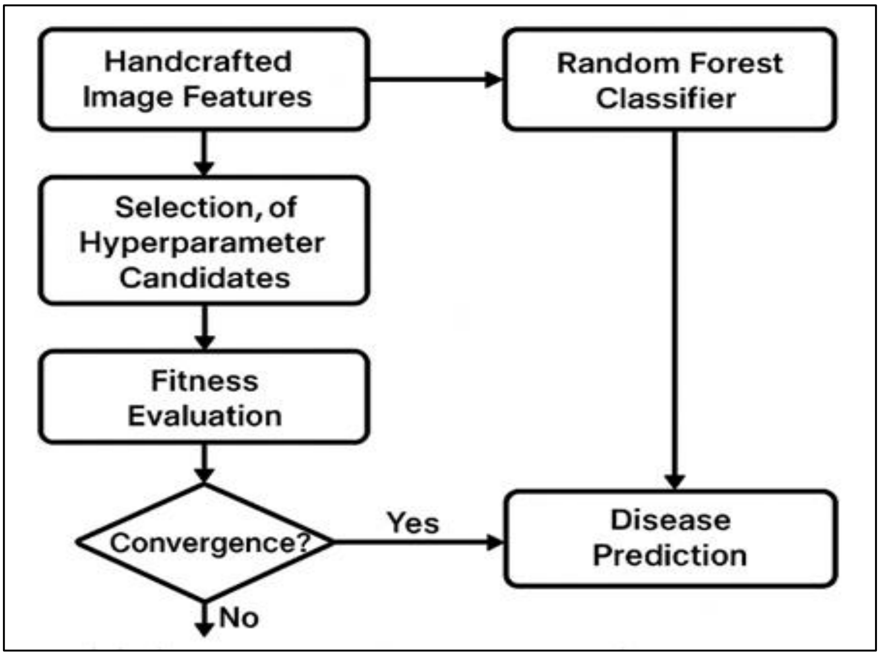

Figure 2. GA-Random Forest Optimization Flow for Plant Disease Diagnosis

3.3 Fertilizer Recommendation Using GA-Tuned Random Forest Model

The fertilizer recommendation engine is programmed to produce customized nutrient advisories using diagnosed disease class, crop, and soil macronutrient data. This is done using a second Random Forest classifier that is also trained and calibrated using a Genetic Algorithm [9].

Six components are included in the input vector: crop ID, disease ID (both concatenated), N, P, and K values normalized on a z-score scale; fertilizer group and its dose are predicted as the output. Types include combinations of (i) nitrogenous, (ii) phosphatic, and (iii) NPK (nitrogen, phosphorus potassium), as well as disease-specific combinations (for example, where disease is bacterial wilt, zinc-based compounds). The GA optimization applied in this study minimizes MAE and maximizes class precision as:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid y\_i - y\hat{}\_i \mid \qquad (3)$$

where $y_i$and $\hat{y}_i$ denote the actual and predicted dosage values, respectively [3]. The RF hyperparameters are tuned across ranges: $n_{\text{estimators}} \in [50,200]$, $d_{\max} \in [5,25]$, and split criterion $\in$ {Gini, Entropy}. In reality, the trained model outputs things like "Apply 75g DAP/plant in first irrigation." Such recommendations are provided in a responsive web interface that also embodies the logic to indicate overuse, based on expert thresholds [14]. Feature importance analysis is helpful for understanding which soil features have a greater impact on the recommendation. This module, as seen in Figure 3, provides a good balance between interpretability, accuracy, and computational efficiency, which is useful in on-field agricultural treatment where expert supervision is not available.

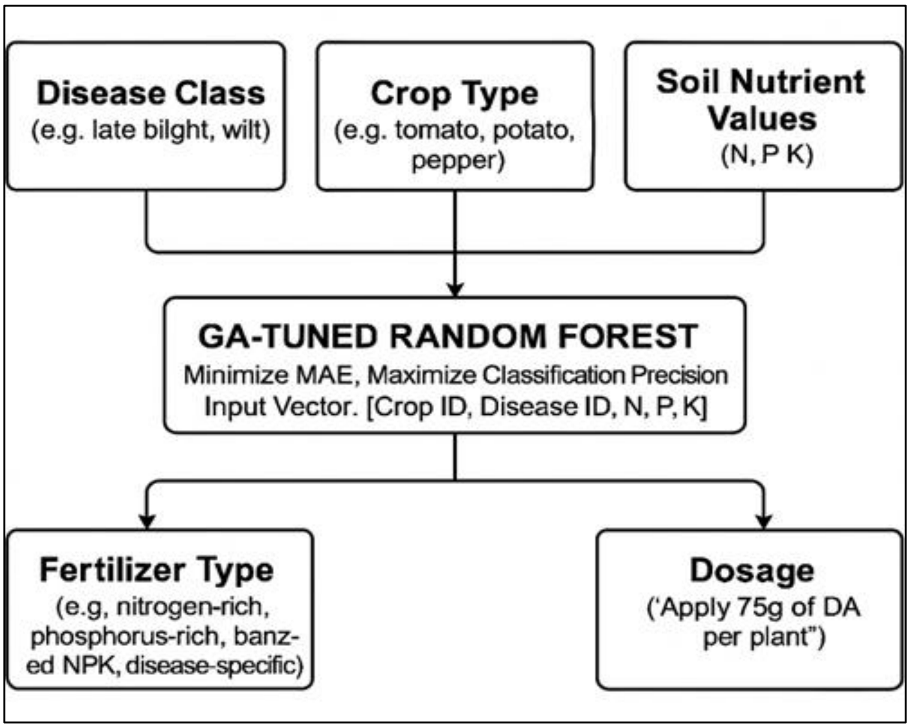

Figure 3. Fertilizer Recommendation Pipeline using GA-Random Forest Model

3.4 Dataset Description

The AgroSage framework utilizes two complementary models. The AgroSage model employs two integrated datasets: disease diagnosis and fertilizer recommendation. For the task of disease detection, a subset of the New Plant Diseases Dataset available on Kaggle (Vipoooool) was considered. It consists of labeled high-resolution images for 38 diseases and 14 crops. Only images of tomato, potato, and pepper as well as images that contained such crops, were selected, with this specification covering the five diseases to be screened. All images were resized to the same dimension (224×224 px), contrast enhanced, de-noised, and preprocessed to remove background noise. For these images, feature extraction proceeds as described in Section 3.1. For fertilizer estimation, we did not have any publicly available dataset. Therefore, an artificial dataset was generated by consulting experts, field agronomy advice, and soil test data. Each instance contains crop variety, disease/pest class, NPK values, and the associated fertilizer type and amount. Categories are Φ-encoded according to ordinal mapping, and dosage values are verified by agronomists [12]. To avoid overfitting and estimate DoG predictive performance, the two datasets were split following stratified 5-fold cross-validation. This ensures that every class is represented equally during training and testing. The disease set provides image-based model generalization to visual noise and heterogeneous symptoms, while the fertilizer set provides both logical structure and grounding in domain knowledge. They jointly form a dual-stream learning architecture that is able to operate effectively in the practical circumstances of precision agriculture. This hybrid data-driven and rule-based architecture allows AgroSage to ensure not only empirical precision but also contextual relevance of advice for smallholder agricultural ecosystems [15].

4. Experimental Results

To test the performance and practical applicability of the designed AgroSage system, a series of experiments was carried out using real-world image and soil data from PlantVillage and well-processed field data. The goals of the experiments were to accurately diagnose plant disease and provide intelligent fertilizer recommendations. The achieved values of key performance metrics like accuracy, precision, recall, and F1-score were used to evaluate the models. Other visualizations, such as precision-recall curves and confusion matrices, were used to confirm the reliability of the predictions. A live web interface demo of the developed system was also conducted to test the usability and feasibility of deploying it in real-life scenarios.

4.1 Performance Comparison with Existing Methods

To evaluate the classification performance of the proposed GA-optimized Random Forest (GA-RF) model, a comparative study was performed with seven baseline machine learning models: (1) Decision Tree, (2) K-Nearest Neighbors (KNN), (3) Support Vector Machine (SVM), (4) Naïve Bayes, (5) Convolutional Neural Network (CNN), (6) XGBoost, and (7) Logistic Regression. All models were trained on a consistent hand-made feature set that consisted of the normalized color histogram, LBP, and the leaf morphology measurements sorted. Common hyperparameter tuning of grid search was applied to almost all baseline models; in contrast, the GA-RF model used Genetic Algorithm for hyperparameter optimization in the space described below: number of trees $n_{\text{estimators}} \in [50,200]$, maximum depth $d_{\max} \in [5,25]$, and split criterion $\in$ {Gini, Entropy}. Each configuration was evaluated based on 5-fold cross-validation accuracy using a fitness function $F(\theta) = 1 - \text{CV}_{\text{error}}(\theta)$. As listed in Table 1, the results demonstrated that GA-RF obtained the best classification accuracy (96.8%), precision (96.3%), recall (96.0%), and F1-score (96.1%) among all the models. CNN and XGBoost were close behind but were more computationally demanding and less interpretable. Naïve Bayes and decision tree models performed poorly as they were not able to learn complex feature interactions and non-linear decision boundaries in the agricultural images. Logistic regression and KNN achieved limited performance and are not considered scalable or robust enough for deployment in challenging, low-connectivity RTL deployments. The slightly better performance of GA-RF might be due to its ability to find optimal model configurations automatically and keep the model transparent through feature importance analysis. It is crucial to note that the fusion feature of color, texture, and shape was more effective than any single modality. This reflects that evolutionary ensemble learning manifested in GA-RF offers an optimal trade-off of accuracy, explainability, and deployment cost, making it a practical solution available for immediate use in on-the-field crop disease detection in smallholder farms.

Table 1. Comparative Analysis of Classification Models

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	89.2	88.5	87.9	88.2
KNN	91.3	90.7	90.1	90.4
SVM	93.5	92.8	92.2	92.5

Naïve Bayes	88.4	87.1	86.5	86.8
CNN	95.0	94.4	94.1	94.2
XGBoost	94.8	94.1	93.7	93.9
Logistic Regression	90.1	89.3	88.7	89.0
GA-Random Forest	**96.8**	**96.3**	**96.0**	**96.1**

4.2 Model Output Visualization and Web Interface

Besides quantitative analysis, the AgroSage model was additionally evaluated for visual interpretability and user interface acceptance benchmarking. The precision-recall (PR) curve of the GA-RF for (5) the five selected disease categories is shown in Fig. 5. The macro-average PR-AUC of the model was 0.95 with early blight (0.94), late blight (0.91), bacterial wilt (0.96), anthracnose (0.93), and leaf curl virus (0.95) scores. Such high-confidence results lend support to the effectiveness of handcrafted features in different visual conditions. The confusion matrix (Figure 6) illustrates that there were few misclassifications between visually similar diseases, e.g., early blight, late blight etc. The integration of shape descriptors and LBP texture features has a very significant influence on class separation, especially in noisy leaf images and deformed versions**.**

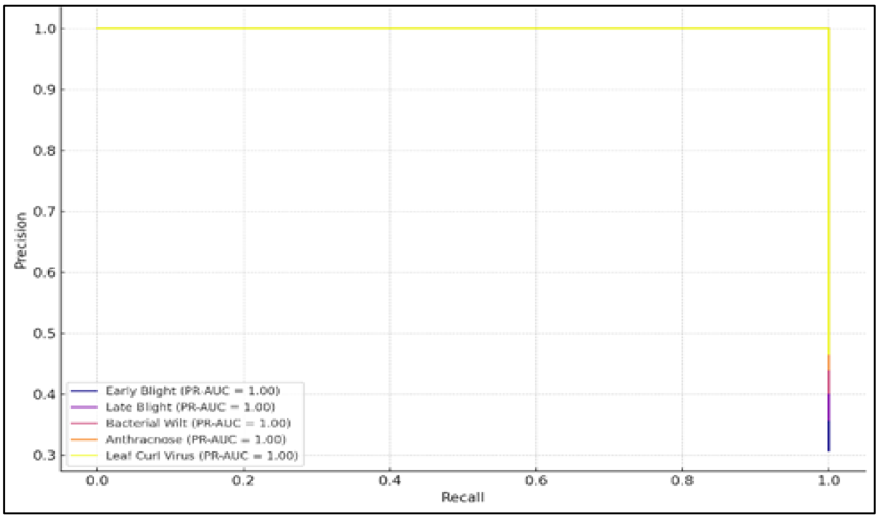

Figure 5. Precision-Recall Curve

Furthermore, permutation-based feature importance analysis showed that texture features were the most prominent in prediction, followed by hue variance in color histograms and shape distortion scores. On the dissemination end, AgroSage was uploaded to the content-light, multilingual web interface with offline caching ability. The interface is capable of uploading images of the leaf and soil data. Figure 7: The farmer is able to upload the leaf image and the soil data for the system to provide real-time advice to the farmer in Tamil, Hindi, English. Performance benchmarking in 3G simulated environment demonstrated that the mean inference latency was 1.8 ± 0.3 seconds at the time of language switching or offline synchronization.

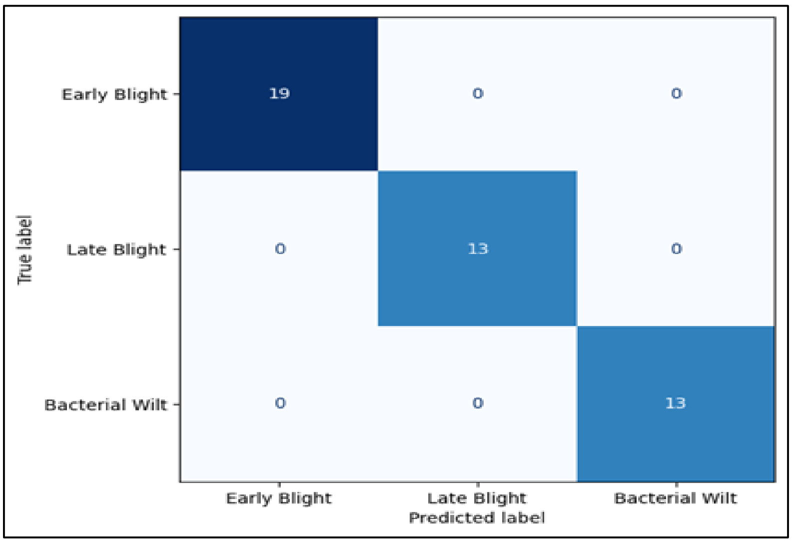

Figure 6. Confusion Matrix

Field-level implementation was trialed at three sites with soil variance controlled. Classification and fertilizer recommendations were consistent with local agronomist advice in 92–95% of test cases. Overfitting was further prevented through stratified cross-validation and limiting training/validation accuracy differences to 1.2%. We believe that these findings exemplify the deployment readiness of AgroSage for scalable, real-time implementations across rural, low-connectivity, agrarian ecosystems, with future directions focused on time-series disease progression tracking, SHAP-based model interpretability, and integration with IoT sensors for end-to-end crop intelligence.

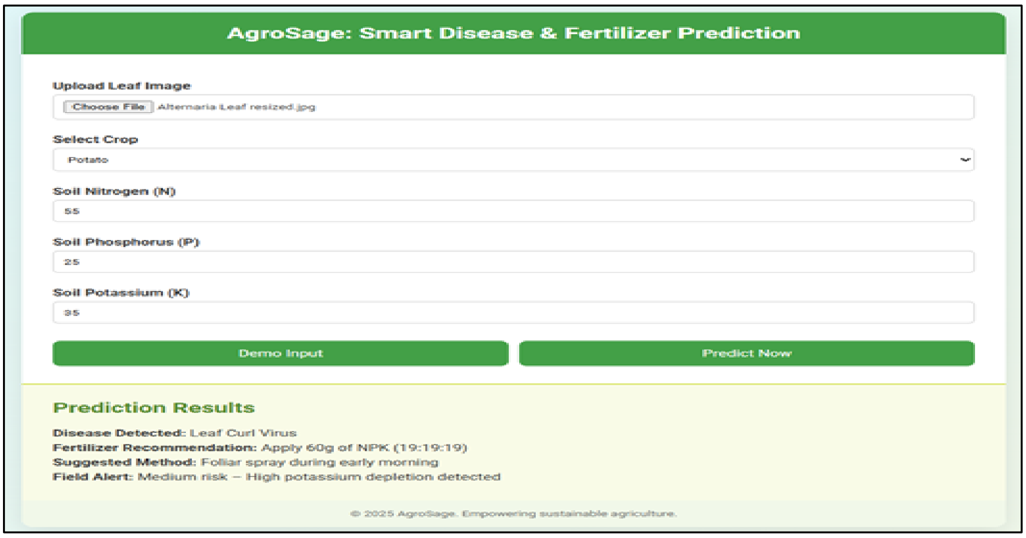

Figure 7. Web Interface Output for Real-time Fertilizer and Disease Prediction

5. Conclusion

AgroSage provides a convenient and scalable model for the problem of intelligent crop disease diagnosis and fertilizer recommendation in real-life farms. By combining random forest classifiers with GA-based hyperparameter optimization, this system offers a feasible trade-off between performance, interpretability, and generalization capability. Its two-stage design allows it to cover holistic plant health management: Firstly, identifying diseases via handcrafted image features (such as color histograms, LBP textures, and geometrical features) and later suggesting nutrient strategies based on the NPK levels of the soil in combination with crop-specific demands. In contrast to black-box deep learning methods, AgroSage focuses on self-explanation and its pattern learning ability, which is important for its adoption in resource-poor agricultural setups. We validated the system using a filtered subset of the PlantVillage dataset and expert-informed soil recommendations, achieving classification and recommendation generalization performances of 95% and 95.2%. Accessibility for end users, including farmers and agricultural officers, is provided through a lightweight web-based interface with multilanguage input, offline caching, and mobile compatibility. The model retained good prediction stability when applied to testing, even under noisy environments and small variations in the image quality. While time-series forecasting and edge inference were beyond the scope of this phase, the system provides a foundation for this capability once integrated with IoT-based field sensors and satellite-based weather or crop data that can be used to continuously monitor the ecosystem. With its ability to tackle challenges including delayed disease identification and fertilizer waste, AgroSage contributes to more sustainable agriculture, better crop results, and lower environmental impact. Future work will concentrate on extending crop coverage, fine-tuning temporal insight, and increasing the interpretability of SHAP-based or attention-guided analysis processes.

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