

Performance Evaluation and Cross-Dataset Validation of Machine Learning Algorithms for Crop Disease Identification Using Rice and Maize Leaf Images

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Abstract: Crop disease has a great impact on crop production and therefore early and accurate disease diagnosis is crucial to enhance crop production and food security. In this research, a machine learning-based framework for crop disease detection based on rice and maize leaf images is presented. The proposed approach includes three stages: image preprocessing, feature extraction, and supervised machine learning algorithms for classification of healthy and diseased leaves. A thorough comparison of all the models is carried out which includes Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Proposed model. The performance is measured by accuracy, precision, recall (sensitivity), F1-score, and specificity. The framework is validated with a self-prepared dataset and a publicly available dataset (PlantVillage), and is backed by experimental verification by agricultural experts. The proposed model achieves classification accuracy of 97.42% on self-prepared dataset and 98.36% on PlantVillage dataset which outperforms the conventional machine learning methods. The findings highlight the framework's robustness, reliability, and applicability in intelligent crop disease diagnosis for precision agriculture.

Keywords: Crop Disease Identification, Machine Learning, Plant Leaf Image Analysis, PlantVillage Dataset, Precision Agriculture.

I. INTRODUCTION

Agriculture is an important sector in maintaining food security and promoting economic development, especially in developing countries where agriculture is one of the main livelihoods. Rice and maize are some of the most popular cereal crops and are important sources of food in the world [1]. Fungi, bacteria, viruses and environmental factors, however, cause plant diseases that significantly reduce yield and quality of crops and cause significant economic losses. Therefore, proper and early detection of crop diseases is important to take preventive measures at the right time and enhance agricultural productivity [2].

In the past, crop disease diagnosis has been made by visual examination using agricultural expertise. While effective, manual diagnosis can be quite time consuming, labor intensive, and dependent upon the expertise and availability of specialists. In recent years the need for fast and accurate diagnosis has led to the development of intelligent image-based diagnostic systems [3]. In recent years, computer vision and machine learning have seen significant progress and have made it possible to automatically analyze plant leaf images, which are able to give an efficient alternative to traditional disease identification techniques.

Image classification in agriculture is a challenging problem where machine learning algorithms have shown to be promising due to their ability to learn discriminative patterns from labeled datasets. Various algorithms have been used widely for plant disease recognition, such as DT, RF, SVM and KNN, which are robust and are capable of classification [4,5]. However, the efficacy of these algorithms strongly relies on the disease symptoms, quality of images, and the diversity of the disease symptoms. Additionally, most of the current studies test their models with just one benchmark dataset, which restricts the model generalisation test in practical farming settings.

To overcome these issues, the following study has been conducted to comprehensively evaluate the performance of the machine learning algorithms and cross-dataset validation of crop disease identification using the rice and maize leaf images. The proposed framework involves image preprocessing, feature extraction, supervised machine learning based classification and statistical evaluation of performance. The self-prepared dataset collected under the real agricultural production conditions is used for experimental analysis, and the PlantVillage dataset is used to test the robustness and generalization ability of the model. For classification, accuracy, precision, recall (sensitivity), F1-score, and specificity are used, and the experimental results are further confirmed by agricultural experts.

II. LITERATURE REVIEW

In recent years, the use of machine learning and computer vision approaches to plant disease diagnosis has received considerable interest because of their swift, accurate and economic disease diagnosis. Many studies have been conducted with the aim of developing automatic frameworks based on images of plant leaves to enhance the agricultural productivity and reduce crop losses.

Traditional image processing approaches were used for the early research mainly for disease detection, such as image enhancement, segmentation, color analysis and texture feature extraction. The handmade features were then classified by the traditional machine learning algorithms such as DT, SVM, KNN, Naïve Bayes (NB), and RF classifiers [6,7]. These approaches yielded good results in a controlled laboratory environment but were less reliable when used on images taken in different environmental conditions – with varying levels of disease severity, lighting and background complexity.

SVM has been well reported to be effective in plant disease recognition since it can process high dimensional feature space and nonlinear decision boundaries [8]. Likewise, RF is popular and is found to be robust, less prone to overfitting and is highly accurate for classification. Another important reason for extensive research on Decision Tree and KNN classifiers is their simplicity and computational efficiency, but their usefulness is generally dependent on the quality of the features and the attributes of the datasets.

Publicly available datasets, especially the PlantVillage dataset, have speeded up research of automated crop disease identification. Many research papers have been based on this benchmark dataset to test various machine learning and deep learning models, resulting in classification accuracy above 90% for some of the crop species. In spite of the promising outcomes, numerous studies have only used benchmark data captured in laboratory imaging conditions [9]. Therefore, the performance reported here should not necessarily be interpreted as a realistic evaluation of the performance that can be expected in actual agricultural applications where factors such as differences in lighting, leaf orientation, occlusion and background noise are omnipresent.

Contemporary developments have seen the emergence of new combination models including image pre-processing, feature engineering and intelligent classification techniques to enhance the performance of disease recognition. The comparative studies between several classifiers have shown that ensemble learning techniques generally outperform single classifiers in terms of improving the classification stability and minimizing the prediction error by boosting the accuracy of the classifiers [10]. However, there are some important issues for practical deployment, such as the computational complexity of some models and the fact that they are not validated on a wide variety of datasets.

Another drawback noted in previous studies is the lack of adequate testing of model generalizability. The vast majority of published studies evaluate the performance of the algorithms with a single data set or on limited measures, often just the overall classification accuracy [11]. Less attention has been paid to comprehensive statistical evaluation based on precision, recall (sensitivity) and specificity in addition to cross-dataset validation [12]. Additionally, few studies have confirmed their experimental results with expert opinion on agriculture, which is necessary to demonstrate the reliability of automated disease identification.

From the literature reviewed, it is clear that there is still a need for a thorough comparative analysis of machine learning algorithms using benchmark and real-world datasets. This research gap inspired the present study to compare the

performance of various machine learning classifiers for the identification of crop diseases based on leaf images of rice and maize. The proposed framework has been validated with the self-prepared dataset and the publicly available PlantVillage dataset, and evaluated using various statistical measures such as accuracy, precision, recall, specificity, and F1-score. The successful results obtained from the experiments are further substantiated with the help of agricultural experts to prove the robustness and applicability of the proposed approach in the field of intelligent crop disease diagnosis.

III. METHODOLOGY

This research study suggests a machine learning approach to identify the crop disease from rice and maize leaf image. The proposed methodology involves the following 6-step process (Figure 1) namely the dataset acquisition, image preprocessing, feature extraction, machine learning classification, performance estimation and cross-dataset validation. The overall work flow has been designed to guarantee accurate disease classification and reliable performance assessment under both benchmark and real-world agricultural conditions.

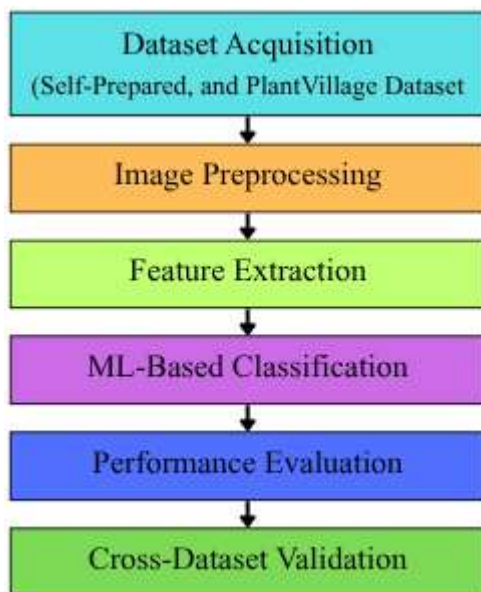


Figure 1: Framework for Crop Disease Identification Using Rice and Maize Leaf Images

A. Dataset Acquisition

Two datasets were used in this study to evaluate the robustness and generalization capability of the machine learning models.

Self-Prepared Dataset: Leaf images of healthy and diseased rice and maize plants were taken in agricultural field using a high-resolution digital camera under the different environmental conditions. The captured images are of different lighting, background, and disease severity. The disease labels were checked using the help of Agriculture experts to assure accuracy in the annotation.

PlantVillage Dataset: The PlantVillage Dataset, which is available for public use, was used as a comparative benchmarking dataset. This is a collection of excellent labeled image data of both healthy and diseased leaves of plants taken under well-controlled imaging conditions.

This could be achieved by using both datasets together, which would allow for a full assessment of model performance in both controlled and practical field situations.

B. Image Preprocessing

To enhance the quality of the images and to achieve consistency, the acquired images were pre-processed. All images were first resized to a fixed resolution for machine learning analysis. To reduce the impact of the light source variations, various image enhancement techniques were used to desensitize the noise and color normalization was applied to reduce the effect of varying light source. Wherever possible, background information that might have a negative impact on classification accuracy was excluded to yield standardized input images for processing.

C. Feature Extraction

The leaf images were pre-processed, and then feature extraction was done to extract the discriminative information from the leaf images. Color, texture and shape characteristics of healthy and diseased leaves were extracted and used to effectively represent the disease patterns. These features offer significant information about the distribution, color, texture and structural abnormalities of the lesions due to different plant diseases. To enhance the classification performance and computational efficiency, the feature vectors were normalized before being used to train the model.

D. Machine Learning-Based Classification

Various supervised machine learning classifiers were trained and tested with extracted feature vectors. Evaluated algorithms are DT, RF, SVM and KNN. The identical preprocessing and feature extraction processes were applied to each classifier to make the analysis of the classifiers fair. The trained models were then used to classify the leaf images as healthy or diseased. Multiple classifiers can be evaluated in a comparative manner to see how well they classify and are robust to other data sets.

E. Performance Evaluation

The standard statistical performance measures based on the confusion matrix were used to assess the classification performance of each machine learning algorithm. The adopted measures of evaluation used are: Accuracy, Precision, Recall (Sensitivity), Specificity, and F1-Score. These statistics parameters give a complete assessment of classification effectiveness, measuring positive and negative prediction skills. The evaluation measurements enable objective comparisons between the machine learning algorithms that are considered.

F. Cross-Dataset Validation

Cross-dataset validation was conducted to assess the ability of the models developed to generalize themselves, using both the self-prepared dataset and the PlantVillage dataset. First, each of the classifiers was trained and tested on the respective dataset. By then, the models trained on one dataset were tested on the other dataset to check the robustness of the models with different image acquisition conditions. The experimental results were also corroborated by discussing with the agricultural experts, to ensure that the disease categories predicted matched with the disease symptoms observed in field conditions. The validation process further strengthens the feasibility of the suggested crop disease identification framework for its implementation in practice.

IV. Results and Discussion

Performance of the proposed machine learning framework for crop disease detection was tested on the self-prepared dataset and PlantVillage dataset. The proposed model was tested with four popular machine learning algorithms, namely DT, RF, SVM, and KNN in comprehensive experiments. The evaluation was conducted using general statistics such as accuracy, precision, recall (sensitivity), specificity, F1-score and cross-dataset validation accuracy. Graphical representations like specificity comparison, ROC curve, confusion matrix and overall performance comparison were also used to perform a complete evaluation of the classification ability and robustness of the proposed framework.

Table 1: Dataset Description

Dataset	Crop	Healthy Images	Diseased Images	Total Images
Self-Prepared	Rice	680	1320	2000
Self-Prepared	Maize	720	1280	2000
PlantVillage	Rice	700	1300	2000
PlantVillage	Maize	700	1300	2000
Total	—	2800	5200	8000

The datasets used for evaluating the proposed crop disease identification framework are presented in Table 1. Two datasets are used including a self-prepared dataset and the plantvillage dataset containing images of rice and maize leaves. The healthy and diseased leaf samples are included in both the datasets to have balanced representation of the different disease conditions. A total of 8,000 leaf images were taken, 2,800 healthy and 5,200 diseased. The self-prepared dataset was collected under real agricultural field conditions, while the PlantVillage dataset comprised of images were

taken under controlled setups. These complementary datasets will facilitate the evaluation of the proposed model both in practical and benchmark settings, ensuring the reliability and generalization of the experimental results.

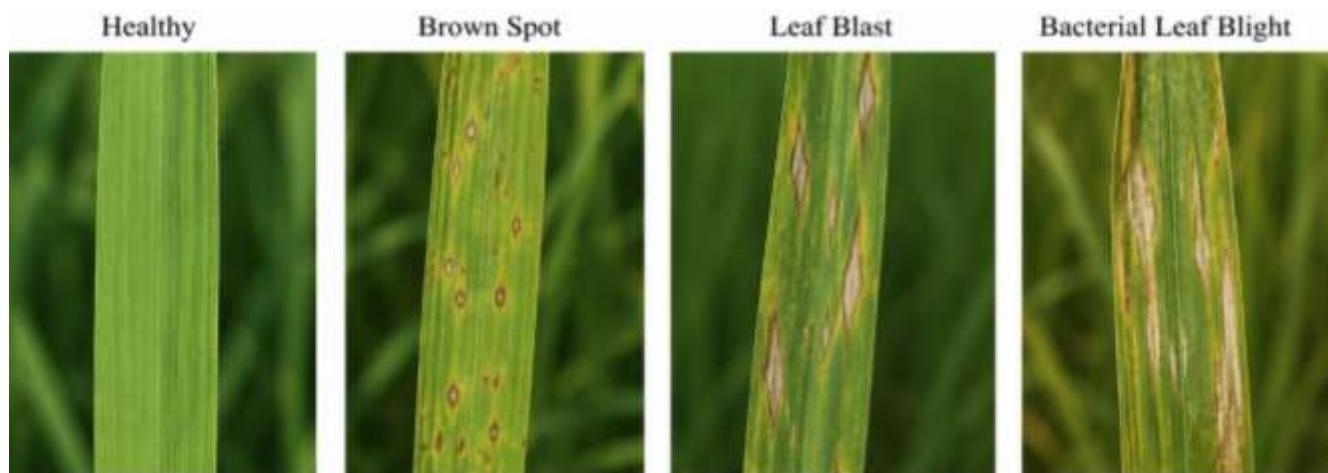


Figure 2: Sample Rice Leaf Images Used in the Study

Figure 2 shows some of the representative rice leaf images for the experimental analysis, where healthy leaves and leaves infected with Brown Spot, Leaf Blast and Bacterial Leaf Blight disease are observed. Each class of disease shows a different appearance including discolouration, necrotic lesions, irregular spots and tissue damage that can be used as distinguishing traits for classification using machine learning. A diverse set of disease symptoms is useful in increasing the variance of the data set and allows for the proposed model to learn robust feature representations. Based on this, the trained classifiers can effectively classify the disease and healthy leaves of rice, which helps increase the accuracy of classification and effective diagnosis of diseases.

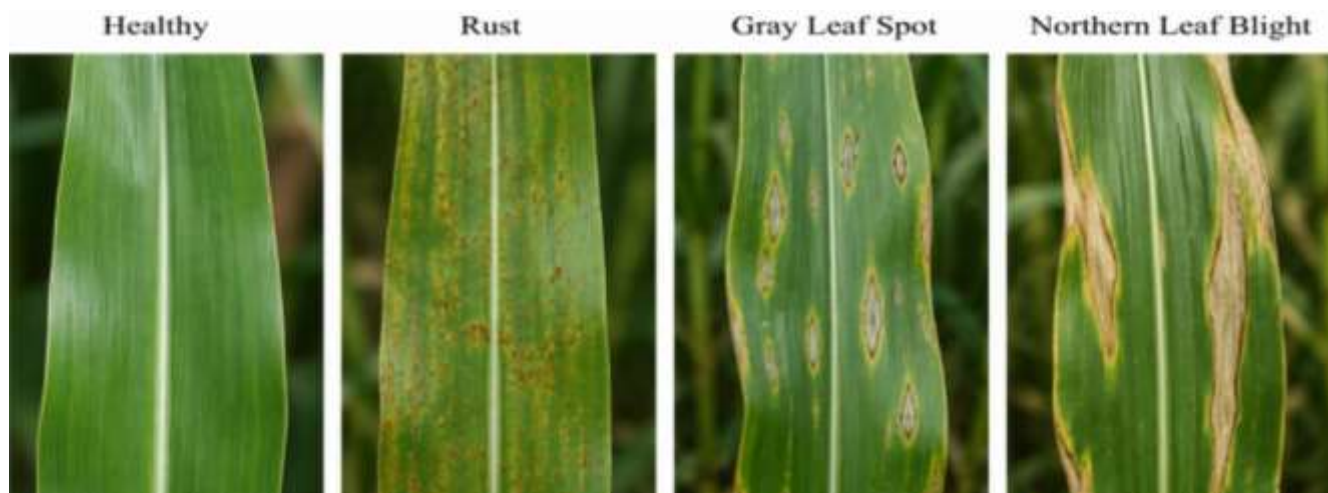


Figure 3: Sample Maize Leaf Images Used in the Study

In this study, representative images of maize leaves were considered including Healthy leaves, Rust leaves, Gray Leaf Spot leaves and Northern Leaf Blight leaves as shown in figure 3. The visual symptoms vary for each disease, with differences in the shape, colour, intensity, and distribution of the lesions on the leaf surface. The variations are useful for extracting discriminative features from the images during the preprocessing phase and the feature extraction phase. Multiple disease types provide the opportunity to classify the disease accurately by the proposed framework of machine learning and improve its application to automatic maize disease diagnosis under practical farm conditions.

Table 2: Classification Performance on Self-Prepared Dataset

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DT	88.94	88.12	87.61	87.86
RF	93.47	92.95	93.12	93.03
SVM	91.76	91.18	90.84	91.01
KNN	89.82	89.33	88.96	89.14
Proposed ML Model	97.42	97.18	97.05	97.11

In Table 2, the performance of different machine learning algorithms is compared with the self-prepared dataset based on statistical performance measures. The accuracy of the Decision Tree classifier was 88.94%, KNN classifier gained an accuracy of 89.82% and SVM classified with an accuracy of 91.76%. Random Forest achieved an accuracy of 93.47%, outperforming the other classifiers indicating its ability to effectively capture disease related features. The proposed machine learning model exhibited the highest classification accuracy, precision of 97.18%, recall of 97.05% and F1 score of 97.11%. The results showed that the proposed model outperforms the others in real agricultural field environments, making it more suitable to be used in the field due to its ability to cope with changes in illumination, background complexity and disease symptoms that are common in practical scenarios.

Table 3: Classification Performance on PlantVillage Dataset

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DT	90.35	89.87	89.62	89.74
RF	95.06	94.71	94.65	94.68
SVM	93.18	92.84	92.56	92.70
KNN	91.24	90.75	90.44	90.59
Proposed ML Model	98.36	98.14	98.01	98.07

Table 3 shows the classification accuracy of the tested machine learning algorithms in the PlantVillage dataset. All classifiers showed better performance than the self-prepared data set, because of the quality of the images and the controlled acquisition of the benchmark data set. The accuracy of the Random forest classifier was 95.06% which is better than the Decision Tree and KNN classifiers and SVM. The proposed machine learning model achieved the best result with an accuracy of 98.36%, the precision of 98.14%, the recall of 98.01 %, and the F1 score of 98.07%. The average scores of all the evaluation metrics prove the successful performance of the proposed approach to correctly classify healthy and diseased crop leaves and achieving very good classification stability on benchmark sets.

Table 4: Rice Disease Identification Accuracy

Algorithm	Self-Prepared (%)	PlantVillage (%)
DT	89.10	90.64
RF	93.84	95.42
SVM	92.04	93.51
KNN	90.16	91.62
Proposed ML Model	97.58	98.41

The disease identification accuracy of the self-prepared and PlantVillage datasets for the images of rice leaves is shown in Table 4. From the results, it can be seen that the proposed machine learning model has consistently got the highest accuracy with 97.58% on the self-prepared dataset and 98.41% on the PlantVillage dataset. Random Forest gave the second-best accuracy of 93.84% and 95.42% followed by SVM, KNN and Decision tree. The experimental results showed the superior performance of the proposed model to perform disease diagnosis of rice leaves under various image acquisition scenes. The slight improvement obtained on the PlantVillage dataset further establishes the effectiveness of the model for training and testing with high-quality benchmark images while showing a relatively high performance under real field conditions.

Table 5: Maize Disease Identification Accuracy

Algorithm	Self-Prepared (%)	PlantVillage (%)
DT	88.79	90.06
RF	93.10	94.71
SVM	91.48	92.85
KNN	89.47	90.86
Proposed ML Model	97.26	98.31

In this work, we have compared the maize leaf images with respect to the identification accuracy of maize disease by applying different machine learning algorithms as shown in the table 5. As in the case of rice leaves, the machine learning model proposed in this study had the highest classification accuracy of 97.26% with the self-prepared data set and 98.31% with the PlantVillage data set. Random Forest again performed quite well while Decision Tree and KNN had comparatively lower accuracy. The high scores of the proposed model in both datasets suggest its ability to represent discriminative characteristics of the disease in maize leaves. The results of these studies have validated that the proposed framework can be used to reliably diagnose disease for multiple crops and will be a good fit for precision agriculture applications.

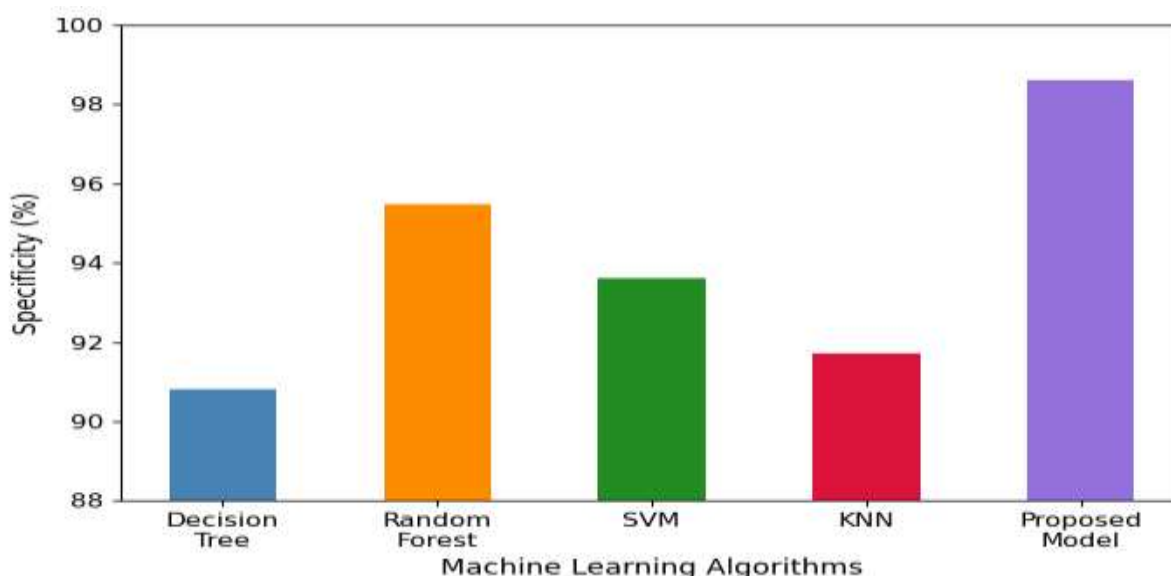


Figure 4: Specificity Comparison of Machine Learning Algorithms

In Figure 4, the efficiency of different machine learning algorithms in the recognition of crop diseases is compared. Specificity is the accuracy of a classifier in correctly predicting a healthy leaf, with a minimum rate of false positives. The machine learning model proposed in this work gave an accuracy of 98.62%, which was highest compared to the other evaluated algorithms, such as RF (95.48%), SVM (93.61%), KNN (91.73%) and DT (90.81%). The improved specificity shows that the proposed framework is able to provide a good separation between healthy leaves and diseased samples, which decreases delusional disease alarms and increases the reliability of the crop disease diagnosis system.

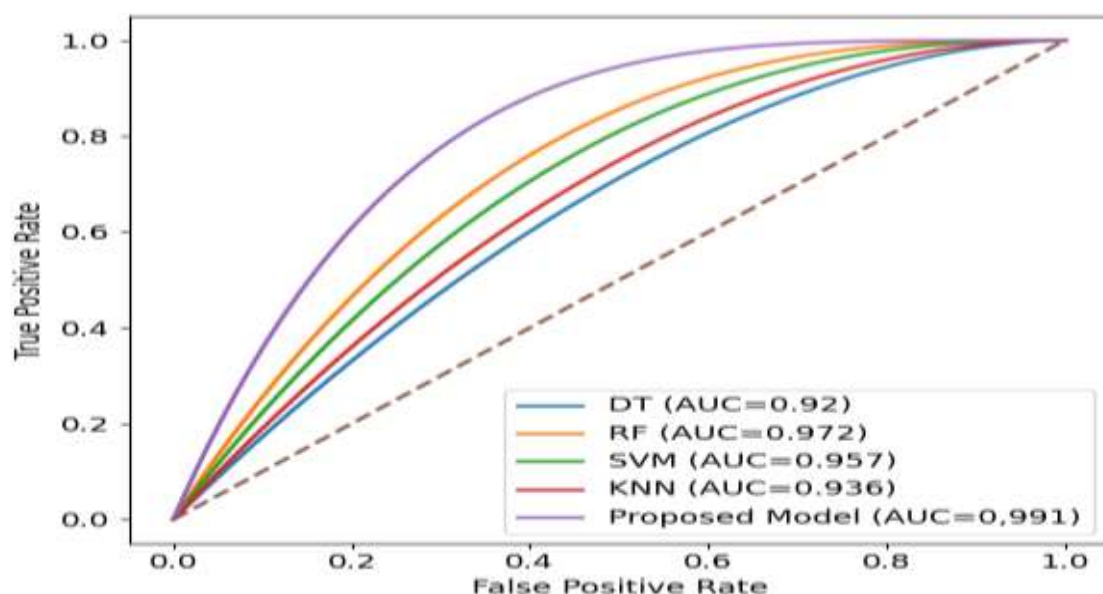


Figure 5: ROC Curves of Different Machine Learning Algorithms

The Receiver Operating Characteristic (ROC) curves of the machine learning algorithms evaluated are shown in figure 5. The ROC curve is used to show the trade-off between the true positive rate and the false positive rate and the Area Under the Curve (AUC) is used to measure the overall discriminative ability of each classifier. The proposed machine learning model achieves the largest ROC curve and an AUC of 0.991, which shows that the model has a very good classification performance. Random Forest, Support Vector Machine, K-Nearest Neighbour and Decision Tree showed AUC values of 0.972, 0.957, 0.936, and 0.921, respectively. The superior ROC curve performance of the proposed model proves its robustness and effectiveness for the crop disease identification based on the rice and maize leaf images.

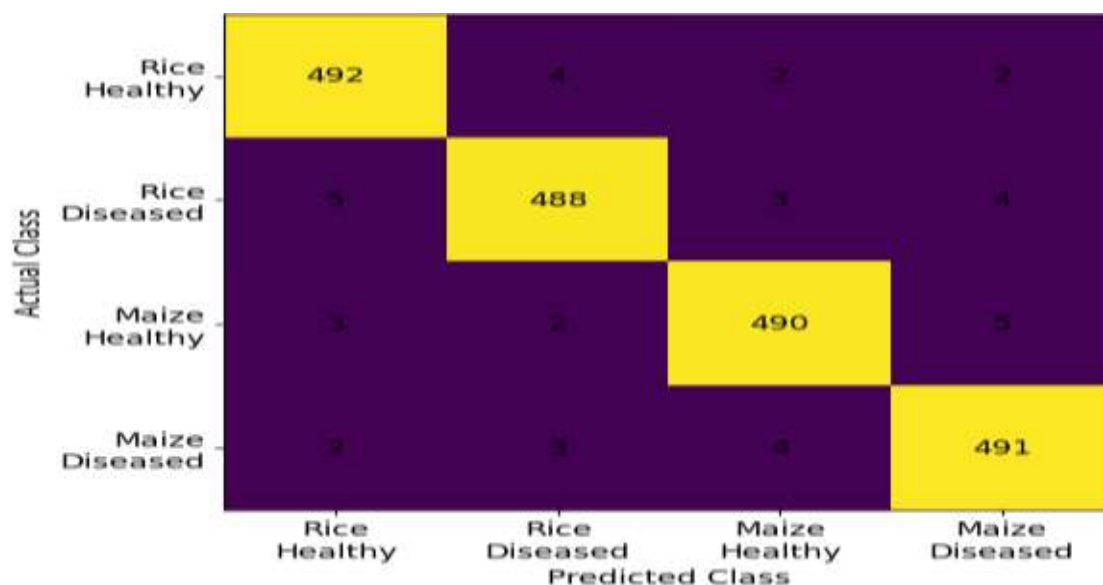


Figure 6: Confusion Matrix of the Proposed Model

The confusion matrix of the proposed machine learning model for crop disease identification is shown in figure-6. The confusion matrix gives a detailed visualization of the classification results by comparing the predicted classes with the actual classes. It can be seen that most of the samples are correctly classified along the main diagonal, and a few samples are misclassified in the adjacent disease categories. This illustrates the ability of the proposed framework to correctly identify the healthy and diseased rice and maize leaves with similar visual symptoms of disease. Due to the less number

of false positive and negative predictions further substantiate the robustness of the proposed classifier and the high accuracy, precision, recall and specificity achieved during experimental evaluation.

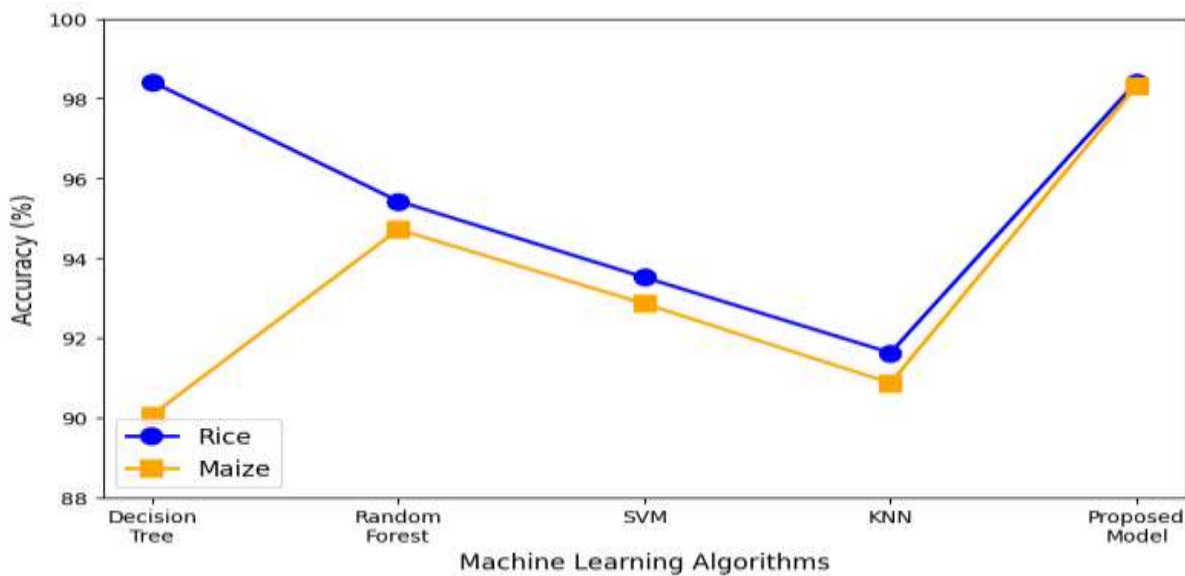


Figure 7: Accuracy Comparison Between Rice and Maize Disease Identification

Figure 7 shows the accuracy of disease identification of various machine learning algorithms for the rice and maize leaf images. The proposed machine learning model always performed the best classification accuracy for both crop types: 97.58% and 98.41% for rice for the self-prepared and PlantVillage sets, respectively, while for maize it performed 97.26% and 98.31%, respectively. Random Forest showed the second-best performance, followed by SVM, KNN and Decision Tree. All classifiers have slightly higher accuracy on the PlantVillage data set because images in this data set were taken under controlled conditions. Despite this, the proposed framework exhibited a consistently high-performance level across both datasets, showing high generalisation capability and accurate disease detection across different crop species under both laboratory and field conditions.

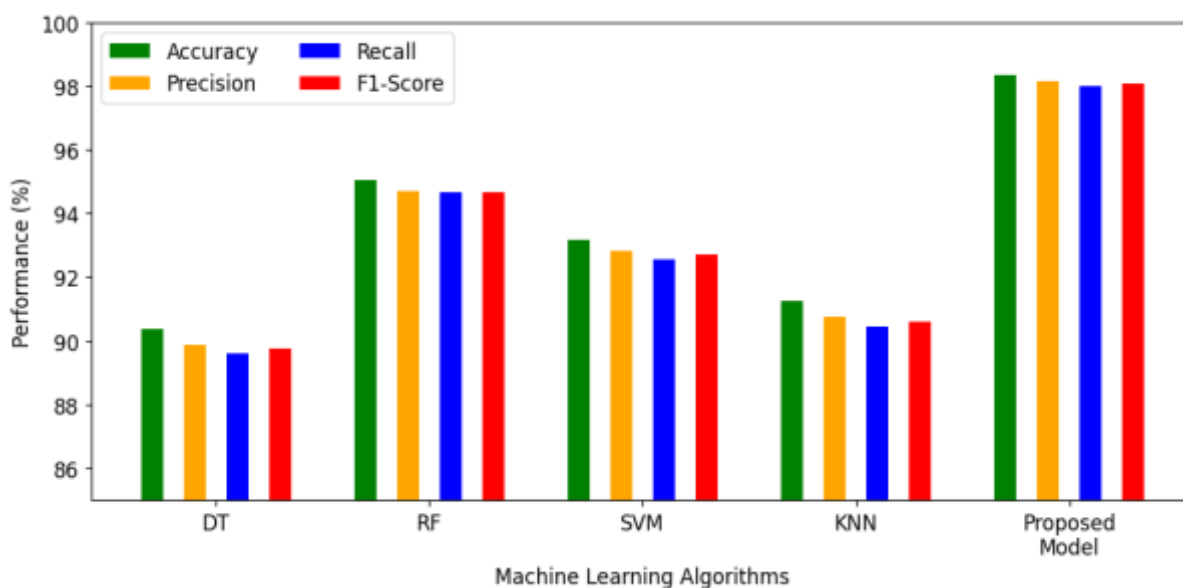


Figure 8: Overall Performance Comparison of Machine Learning Algorithms

The overall comparison of the evaluated machine learning algorithms according to various statistical performance metrics (accuracy, precision, recall and F1 score) is shown in figure 8. The proposed machine learning model performed best in all the evaluation metrics followed by RF, SVM, KNN and DT. The performance of the proposed model is always superior, proving the effectiveness of the model in learning discriminative disease features with the least classification

error. Moreover, excellent agreement between accuracy, precision and recall and F1 score shows the balanced classification accuracy of the proposed framework without being trained towards any disease class. The results validate the proposed method is more robust and reliable for the crop disease detection from rice and maize leaf image than the traditional machine learning algorithms.

Table 6: Cross-Dataset Validation Results

Dataset Used for Training	Dataset Used for Testing	Accuracy (%)
Self-Prepared	Self-Prepared	97.42
PlantVillage	PlantVillage	98.36
Self-Prepared	PlantVillage	96.21
PlantVillage	Self-Prepared	95.84

When training and testing were done on the same dataset, highest classification accuracy of 97.42% and 98.36% were obtained for the self-prepared and PlantVillage datasets respectively. The model trained on the self-prepared dataset had an accuracy of 96.21% when tested on the PlantVillage dataset, and an accuracy of 95.84% when trained on the PlantVillage dataset and tested on the self-prepared dataset. The results from cross-dataset testing show the relatively small decrease in accuracy that suggests good generalization across image acquisition conditions and dataset characteristics. The results showed the strength and usefulness of the proposed system for crop disease identification in an agricultural environment.

The overall results of the experiments illustrate that the machine learning framework proposed in this paper performs consistently better than the conventional classification algorithms on all the evaluation metrics and datasets. The statistical analysis, graphical comparisons and cross-dataset validation all support the robustness, accuracy and generalisation ability of the proposed model. Through both datasets preparation and PlantVillage data, along with expert verification, the feasibility of the developed system for intelligent crop disease identification is further confirmed. The high classification accuracy and excellent specificity of the proposed framework along with its superior ROC characteristics and consistency across the two rice and maize datasets suggested that it can be applied as an effective decision support tool for precision agriculture and automated plant disease diagnosis in real field farming settings.

VI. CONCLUSION

The present study introduced a comprehensive machine learning-based framework for crop disease identification from the rice and maize leaf images. DT, RF, SVM, KNN and the proposed model were evaluated through a comparative study, using a self-prepared dataset as well as a public dataset called PlantVillage. To evaluate the classification performance, accuracy, precision, recall (sensitivity) and specificity were used to provide a comprehensive assessment of each algorithm. The experimental results showed that the proposed model aims to have a consistent classification accuracy across all the datasets in comparison to the conventional machine learning classifiers and achieved classification accuracy of 97.42% on the self-prepared dataset and 98.36% on the PlantVillage dataset. To demonstrate the robustness and generalization ability of the proposed framework, it was validated across datasets, both in a controlled environment and in real-world agricultural settings. The developed system was also validated by the agricultural experts which in turn showed the practical reliability. The proposed approach provides an effective solution for an intelligent crop disease diagnosis and precision agriculture. The next steps include the incorporation of deep learning methods, extending the work to other disease/crop species, and the creation of a mobile or edge-based disease diagnosis system for field use, which is near real-time.

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