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Original Article

AI-Driven Identification of Rice Crop Disorders Using Multi-Model Classification Framework

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Abstract - *Cultivated in many nations across the globe, rice is a staple food of great importance. Rice leaf diseases can severely affect crop cultivation, resulting in low crop yields and financial losses. In an older method of identifying leaf diseases, they are classified based on their color, morphology, texture, and shape. Fully automated instructional systems can quickly identify diseased leaves with minimal human assistance. Most of the earlier research on identifying leaf diseases in rice crops used machine learning and feature extraction methods. Characteristics like its shade, surface, patterns of veins, and lesion extent were retrieved from photos of sick leaves. Stated differently, machine learning identifies the illness by extracting characteristics. Instead, machine learning-based feature vector extraction is not totally superior because it involves retraining and missing one dimension. The proposed hybrid model predicts the diseased leaves of rice crops with 97% accuracy and minimum training and validation losses of 0.80 and 1.25, respectively.*

Keywords - *Accuracy, CNN, Disease Detection, Rice Leaf, SVM.*

1. Introduction

Rice is among the key staple crops for many people around the globe, and agriculture has been a big part of food security. Environmental conditions, farming practices, and biological stresses that include leaf diseases are the major factors that determine the production and excellence of rice crops. Pathogenic fungi, bacteria, and viruses cause diseases that result in a high level of yield loss, poor quality of the grain produced, and significant losses incurred. Moreover, due to the late detection of diseases, the overuse of pesticides that harm the soil, ecosystems, and the well-being of people usually occurs. Therefore, the challenge of early and effective detection of rice leaf diseases is paramount in ensuring increased crop yield and the enhancement of sustainable agricultural activities. Traditionally, rice disease has been identified using visual inspections of an infected region or crop by an experienced farmer or agricultural expert according to manual [1] guidelines and reference material. Although this is an approach that is mostly applied, it is highly time-consuming and subjective, and is highly likely to be influenced by human errors. The disease's symptoms can often be seen late in the infection, limiting the chance for timely action. Most rural and remote areas have restricted availability of agricultural specialists, further compounding the difficulty. These constraints emphasize the necessity of automated and smart disease detection systems to assist farmers in timely decision-making [2]. The development of computer vision has seen several automated methods for detecting illness in rice leaves through image processing and AI methods.

These methods employ preprocessing of rice leaf images to filter out poor-quality images, and feature extraction is done manually using color histograms, texture descriptors, and shape analysis. These are the features that are extracted, and they are then classified with machine ML algorithms. While these methods have demonstrated good performance, they are largely subject to handcrafted features and domain knowledge. Moreover, handcrafted features tend to miss complicated patterns of disease in a changing light setting, cluttered backgrounds, and disease severity, which restricts the strength and generalization in the real-world setting. The use of deep learning has become a potent substitute for disease detection based on images, as it is able to automatically learn hierarchical and discriminative features directly out of raw images. CNNs have shown high performance in many different agricultural and medical imaging problems, as they are able to capture spatial patterns and textures as well as disease-specific patterns. Nevertheless, end-to-end CNN-based classifiers may demand large, labeled images and large computational resources. Furthermore, the overfitting of fully connected layers of classification in CNNs can be a problem when the available training data are limited or imbalanced-scenarios typical of agricultural data [3].

Research Gap and Technical Motivation: In a thorough analysis of the literature, it has been noted that, despite CNNs being superior in the extraction of features, their classification capabilities can be improved by incorporating the use of powerful traditional classifiers. On the same note, SVM classifiers are reputedly known to have a high generalization performance and do well in high-dimensional feature space; however, their performance is also limited by the quality of the input features [4].

The current research in detecting illnesses in rice leaves seldom uses the synergistic benefits of CNN-based deep feature representation and SVM-based classification in a single system. In addition, most of the studies concentrate on a few types of diseases and do not provide a complete comparison of performance to the most advanced methods.

Proposed Approach and Novelty: This piece suggests a hybrid CNN-SVM system to overcome these shortcomings and detect rice leaf disease. The suggested technique uses a CNN model to automatically detect deep and discriminative features in rice leaf pictures without needing to comprehend the features, which is what manually designing features is for. Such deep features are then introduced into an SVM classifier, which classifies the disease with better generalization and strength. The suggested method integrates the feature learning ability of CNNs with the ability to classify data as powerfully as SVMs, leading to high precision and high stability. Besides, the framework is tested on five different rice leaf diseases and otherwise widely in contrast to the current cutting-edge tools to confirm the effectiveness of the framework [5].

2. Diseases in Rice Leaf's

Table 1 presents major rice diseases along with their causes, characteristic symptoms, and impact on rice crop productivity. This information provides a concise understanding of disease severity and its implications for yield loss and crop health management.

Table 1. Types of diseases in rice leaf

Disease Name	Cause	Symptoms	Impact
Bacterial Leaf Blight	Leaf blight caused by bacteria, Oryzae pv. Xanthomonas oryzae is spread by infected seeds, wind-driven rain, and contaminated water. Insect vectors and farm tools also facilitate infection, and threaten crop health and productivity.	Bacterial Leaf Blight starts with lesions bathed with water on leaf margins that turn yellow and brown, eventually forming streaks. In severe cases, seedlings wilt, dry out, and may die due to the "Kresek" symptom.	Bacterial Leaf Blight can cause up to 50% yield loss, reducing grain quality and weight. It also increases susceptibility to secondary infections, leading to economic losses for farmers.
Blast	It is a wind-borne, rain splash-borne, seedborne, and residue-borne fungal disease. Magnaporthe oryzae, also known as Pyricularia oryzae, is the fungal pathogen that favors warm temperatures of 20–30°C with high humidity.	Blast disease causes small, spindle-shaped lesions with grayish centers and brown borders on leaves, leading to drying and wilting. Severe infection affects nodes, causing "node blast" and stem breakage, while grain infection results in poor seed development.	Blast disease can cause severe yield losses, exceeding 70% under favorable conditions, while also reducing grain quality and market value. Infected plants become weak, prone to lodging, and more vulnerable to secondary infections.
Brown Spot	The fungus pathogen Brown spot sickness is caused by Bipolaris oryzae. It is transmitted by the use of infected seeds and spores in the air. It is spread by poor soil nutrition, inadequate amounts of nitrogen and potassium, a humid environment, and an extended wet period of the leaves.	Brown spot disease is an AI disease that is characterized by small oval or circular brown lesions with grayish centers on the leaves, which become enlarged and result in leaf lightening and drying. The illness also causes brown spots on the grains, and this impacts the seed quality, and extreme infections can cause seedling blight, retarded growth, and poor tillering.	Under favorable conditions, Brown spot disease may result in serious yield losses of over 70 percent, unsatisfactory grain quality, and low market value. Plants that have become infected are weak, can be easily lodged, and are exposed to secondary infections.
Sheath Blight	The fungal pathogen Rhizoctonia solani causes sheath blight, although its spread is caused by the presence of infected plant debris, contaminated soil, aerial, and waterborne spores.	Brown spot disease manifests itself as small oval or circular brown spots with grayish centres on leaves, causing leaf blight and drying. Severe infections cause brown	In favorable conditions, brown spot disease may result in losses of yields up to 70 percent, low quality of the grain, and low market value.

	High density and nitrogen fertilizer encourage sheath blight disease to thrive, and this results in an environment that is humid, which facilitates the growth of fungi.	grains, which affect seed quality, seedling blight, impaired growth, and reduced tillering.	Plants affected end up being weak and likely to lodge, making them susceptible to subsequent infections.
Tungro	The fungus Rhizoctonia solani, which causes sheath blight, spreads by contaminated soil, plant detritus, and airborne or watery spores. High density and excess nitrogen fertilizer create a favorable humid environment for its growth.	Infected plants exhibit stunted growth with fewer tillers and yellow to orange discoloration of leaves that begin at the tips. Additionally, there is reduced leaf size, delayed maturity, and poor panicle development resulting in unfilled grains.	Yield loss from severe infections can reach up to 100%, resulting in poor grain quality and reduced market value. Additionally, increased production costs for pest control and weakened plants contribute to their heightened susceptibility to other diseases.

3. Related Work

Tejaswini et al. [6] suggested a technique of diseased classification of rice leaves via CNN that would early detect and diagnose diseases to take preventative measures in time. They combine a 5-layer CNN with popular instances of DL with VGG19, VGG16, Xception, and ResNet, and classify four rice illnesses based on images. Zeng et al. [7] suggested an accurate method of classifying rice disease according to ICAI-V4 with improvements in terms of the Candy algorithm to cut off image noise but accentuate edges. This coordinated focus-based approach was found to be more accurate in contrast to alternative models, like AlexNet and ResNet50, as it was tested on 10,241 images with 10-fold cross-validation.

Simhadri and Kondaveeti [8] used transfer learning to detect rice leaf illnesses using already trained DL models. This is an algorithm that refines a large dataset model to a smaller task-sensitive model, enhancing illness detection accuracy. The paper by Sudhesh et al. [9] has proposed the DMD method, which has been evaluated in terms of 10 deep CNN models that have been trained on transfer learning. The effectiveness of such a method was demonstrated by DenseNet121, which, in terms of illness localization, outperformed other models.

Aggarwal et al. [10] put forward an approach of forecasting rice leaf diseases on a deep learning basis. Their method logged a high accuracy level of 0.94 using the EfficientNetV2B3 classifier by using 32 models that were pre-trained and ensemble learning, which proves that their technique is effective when it comes to identifying rice illnesses.

Rajpoot et al. [11] investigated the application of the deep architecture of Faster R-CNN and VGG-16 to identify three major diseases in rice. Their algorithm, which was assisted by a random forest classifier, was found to have 0.97 prediction accuracy, and this was an effective solution to the disease detection. Senan et al. [12] further proposed a 5-layered CNN that distinguishes between four various disease classes: brown spot, leaf blast, hispa, and healthy. It is successful with a 93% accuracy rate. In order to extract and classify features, hybrid methods are also used by merging multiple models, which could be one or many different kinds of models. This helps in solving more complex problems that could not be solved by a single model.

Mannepalli et al. [13] introduce a technique for diagnosing rice leaf diseases using the convolutional neural network VGG16, attaining 97.77% accuracy in categorization on a publicly accessible dataset, thereby illustrating its applicability for the purpose of precision farming. Stephen et al. [14] created a 3D2D DCNN for classifying rice diseases by integrating a 2DCNN for features with a better backtracking search method. The result was 98.7% accuracy.

Kaur et al. [15] suggest the use of a DL-based method for detecting rice leaf disease through the pre-trained models, including VGG16, SqueezeNet, and InceptionV3. Of them, SqueezeNet has an accuracy of 93.3, which is the highest. The purpose of the model is to accomplish timely and accurate interventions to reduce both ecological and economic effects.

Kulkarni and Shastri [16] cover the use of image processing and ML in the detection of rice leaf disease. A novel CNN model may be used to identify the prevalent diseases with 95% accuracy under different lighting and backgrounds, and this indicates the potential of machine learning in assisting farmers in managing diseases.

The article by Mukherjee et al. [17] gives an extensive overview of the methods used to identify and classify rice leaf disease. It includes visual features, image mode, image obtaining, image processing, image features, machine learning algorithms, and handheld applications for detecting time.

Table 2 below provides a comparison of existing studies on rice crop disease identification, highlighting the datasets used, classification techniques, and performance metrics reported by different authors. The Comparison reveals that recent approaches increasingly employ deep learning models to improve classification accuracy, although variations in datasets and experimental settings limit direct performance comparison.

These observations motivate the need for a robust multi-model classification framework capable of achieving consistent performance across diverse rice crop disorder datasets.

Table 2. Comparative analysis of existing studies on rice crop disease identification

Author(s) & Ref.	Methodology / Model Used	Dataset Details	Diseases	Key Findings / Performance
Tejaswini et al. [6]	Custom 5-layer CNN, VGG19, VGG16, Xception, ResNet	1600 rice leaf images	Classification of 4 rice diseases	Custom 5-layer CNN achieved the best performance among all models, enabling early disease detection.
Zeng et al. [7]	ICAI-V4 with Candy algorithm, coordinated focus strategy	10,241 images, 10-fold cross-validation	Rice disease categorization	Outperformed AlexNet and ResNet50 in accuracy by reducing noise and enhancing edge features.
Simhadri & Kondaveeti [8]	Transfer learning with 15 pre-trained CNN models	Not specified	Rice leaf disease identification	Fine-tuned models improved detection accuracy on limited datasets.
Sudhesh et al. [9]	Dynamic Mode Decomposition (DMD) + transfer learning	Not specified	Disease localization	DenseNet121 achieved superior localization performance among 10 CNN models.
Aggarwal et al. [10]	32 pre-trained DL models + ensemble classifiers	Not specified	Rice leaf disease forecasting	EfficientNetV2B3 achieved 94% accuracy, demonstrating strong diagnostic capability.
Rajpoot et al. [11]	Faster R-CNN, VGG-16 + Random Forest	Not specified	Detection of 3 rice diseases	Achieved 97% prediction accuracy, proving effective disease detection.
Senan et al. [12]	Custom 5-layer CNN, hybrid multi-model approach	Not specified	Brown spot, leaf blast, hispa, healthy	Achieved 93% accuracy; hybrid modeling improved complex disease classification.
Mannepalli et al. [13]	VGG16 CNN	Publicly available dataset	Rice leaf disease classification	Achieved 97.77% accuracy, highlighting applicability in precision agriculture.
Stephen et al. [14]	3D–2D Deep CNN + backtracking search algorithm	Not specified	Rice disease classification	Achieved 98.7% accuracy using combined spatial–temporal features.
Kaur et al. [15]	VGG16, SqueezeNet, InceptionV3 (DL models)	Not specified	Rice leaf disease detection	SqueezeNet achieved the highest accuracy of 93.3%, supporting timely interventions.
Kulkarni & Shastri [16]	Image processing + ML, custom CNN	Not specified	Common rice diseases	Achieved 95% accuracy under varying lighting and background conditions.
Mukherjee et al. [17]	Comprehensive review (ML, DL, mobile apps)	Multiple datasets reviewed	Rice leaf disease identification	Provided extensive analysis of imaging, feature extraction, ML/DL techniques, and real-time systems.

4. Methodology

This paper will suggest a deep learning and machine learning hybrid model to identify and categorize rice leaf diseases with image data.

The general process of the proposed methodology includes data acquisition, preprocessing, feature extraction with the help of the proposed methodology.

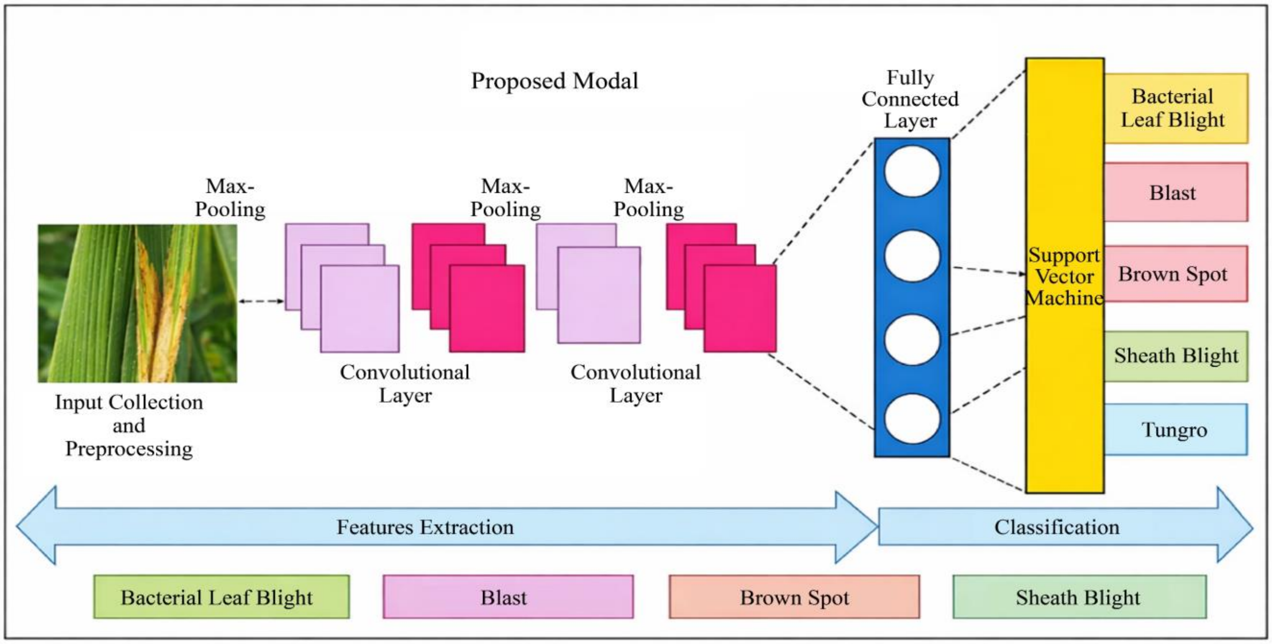

Fig. 1 Schematic representation of the proposed model

4.1. Dataset Description

The analysis of the experiment is undertaken with reference to a publicly available dataset of rice leaf disease images, which were taken on the Kaggle portal. The dataset is made from 3158 RGB pictures of five different classes of rice leaves, such as healthy and diseased.

The images have real-life differences in terms of illumination, background, and severity of the disease, which is why the dataset is appropriate to assess the efficiency of the suggested model. (Figure 2) shows different sample images of each category of disease present in Rice Leaves.

Fig. 2 Different diseases in rice leaves

4.2. Data Preprocessing

A detailed image processing pipeline is used before feature extractors so that the architecture can be compatible with deep learning and enhance model generalization. To minimize the computational complexity and consistency across samples, images are all resized to a common resolution. The centering of the leaf area and normalization of the orientation are then done to the leaf area to reduce background interference [18].

4.3. Feature Extraction using Convolutional Neural Network

A Convolutional Neural Network (CNN) is used as an automatic feature extractor because it is found to be effective in learning multi-level representations with regard to image data. Multiple convolutional layers make up the CNN architecture. It has layers of pooling and non-linear activity functions, which allow obtaining both high-level and low-level characteristics [19].

CNN has been found to pick up basic visual properties like edges, color changes, and contours in the first few layers. The deeper the network, the more intricate and more disease-specific features are learned, e.g., lesion shapes, texture patterns, and spatial distributions. The pooling layers gradually decrease the spatial dimensionality of the data without losing any critical information and, consequently, increase feature robustness.

Rather than classifying the data directly via the CNN's fully linked layer, the deep feature vectors that have been obtained in the last convolutional layer are then passed through an external classifier to enhance the discrimination.

4.4. Disease Classification using Support Vector Machine

To apply to the last disease classification, SVMs, or support vector machines, are utilized using deep features created in a CNN. SVM is a supervised machine learning algorithm that finds the best hyperplane to maximize the margin between classes, and SVM-based classification is also integrated to increase the performance of the classification as well as its various types of disease in the feature space. With a marked training dataset, the SVM gets trained to project the features extracted onto the disease classes.

It is especially applicable to hybrid deep learning models due to its capability to address the high-dimensional feature spaces as well as minimize overfitting. CNN-based feature extraction generalization is particularly useful when there is a small or imbalanced dataset.

4.5. Hybrid CNN-SVM Framework

The proposed hybrid model will have the benefits of representation learning with deep neural networks and the high decision boundaries of classical machine learning classifiers. This feature of the learning/classification dichotomy allows more effective control of the learning process and leads to enhanced detection of the disease in contrast to the use of CNN classifiers alone.

4.6. Performance Evaluation

F1-score, recall, accuracy, precision, and confusion matrix analysis are the common performance metrics that are used to determine the effectiveness of the proposed model. These measures show a detailed evaluation of how the model effectively detects various rice leaf diseases and reduces the rate of misclassification [20].

5. Results and Discussion

The trials' outcomes demonstrate the efficiency of the suggested CNN & SVM method. The results of the proposed CNN+SVM can be improved by varying a few parameters.

However, Table 2 lists some of the more significant ones in relation to the numbers selected. The same parameters are used to train proposed CNN+SVM models and other pretrained architectures.

Table 3 below shows the hyperparameters and training configuration. The details included consist of the number of epochs, batch size, loss function, and distribution of the dataset. The further dataset has been partitioned into different multi-part datasets.

Table 4 shows and summarizes the proposed model's class-wise performance in terms of different performance metrics. Parameters also highlighted the model's ability to find the different existing diseases.

Table 3. Model training parameters

S.NO	Parameter Used to Train Model	Value
1	Frequency of Epoch	100
2	Group Size	32
3	Loss Function	Categorical Cross-Entropy
4	Training	60%
5	Validation	24%
6	Testing	16%

Table 4. CNN+SYM classification report

S.No	Disease Classes	a (%)	b (%)	c (%)
1	Bacterial Leaf Blight	96	98	97
2	Blast	98	96	97
3	Brown Spot	96	97	97
4	Sheath Blight	98	95	97
5	Tungro	98	95	97
6	Accuracy			97
7	Macro Average	97	96	97
8	Weighted Average	97	97	97

5.1. Analysis of Research Findings

The prime objective of the study is to categorize several rice plant leaf diseases by using the dataset classified by the CNN+SVM model. The whole quantity of images gathered following the data reduction procedure is used to calculate the findings [18]. An investigation was conducted using the proposed CNN+SVM model, which achieved the best overall accuracy, using 60% of the training, 24% of the validation, and the remaining 16% of the testing images, respectively. The results show that 97% of training, validation, and testing accuracy was achieved after training the CNN+SVM model. The loss of 0.80 for training and 1.25 for validation was also found. The (Figure 3) above shows the variation of training and validation loss over 100 different rounds for epochs. A steady decrease in the loss of training parameter shows the effective learning and convergence of the model.

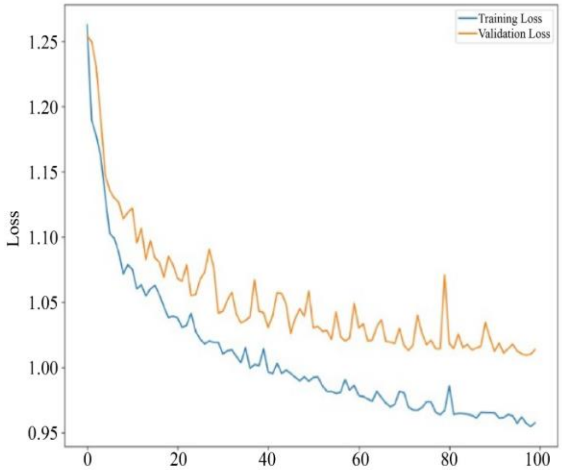

Fig. 3 Training and validation loss

The progression of accuracy of training and validation over 100 epochs is shown above in Figure 4. The training parameter accuracy increases steadily, showing effective learning. The validation curve also follows the same path with some minor fluctuations.

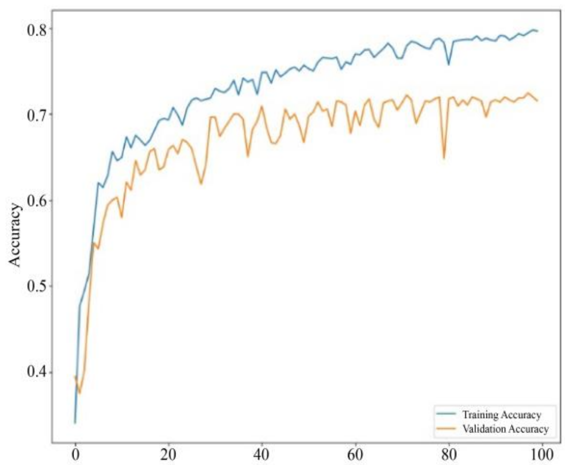

Fig. 4 Training and validation accuracy

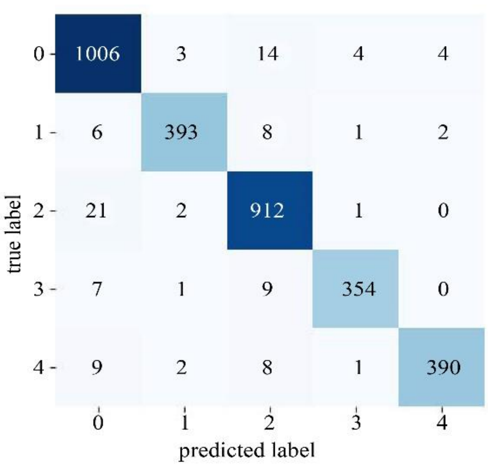

Fig. 5 Confusion matrix

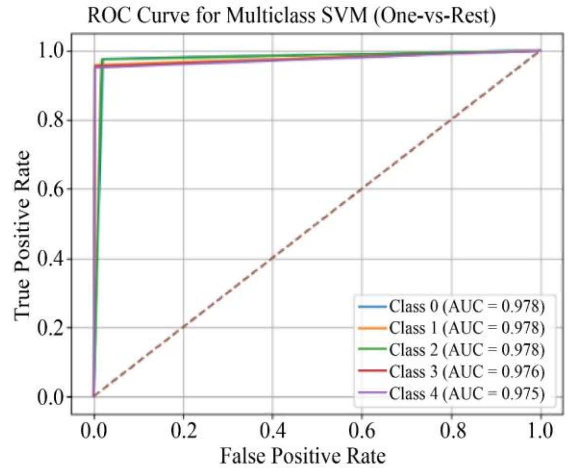

Fig. 6 ROC curve of SVM model

Table 5. Comparative analysis

Model		Accuracy
Pre-Trained	Efficientnet B2V3	94%
	XceptionNet	94.33%
	Faster RCNN	83.78%
Hybrid	CNN+SVM	96.80%
	RCNN+VGG16&RF	96.30%
	Proposed CNN+SVM	97%

6. Conclusion and Future Work

The rising prices of production factors in agriculture, the decreased soil fertility composed of various minerals, and the tightening of the regulations have increased the introduction of artificial intelligence solutions in the modern agricultural sphere to improve the output and reduce losses in crops. Plant illnesses have a great influence on the quantity and quality of crops, especially those crops that are staple foods like rice.

Without the help of specialists in a timely manner, farmers usually suffer significant economic losses when they identify diseases incorrectly and receive incorrect treatment. Furthermore, the deficiency of a full body of information about the biodiversity of plant leaf diseases further stresses the need to develop an accurate and automatic system for diagnosing the disease.

The proposed study is a hybrid CNN-SVM model that will classify five categories of rice leaf disease based on image data. The CNN is effective in extracting the discriminative deep features of rice leaf images, and the SVM classifier is used to guarantee strong and accurate disease classification.

The experimental findings indicate that the proposed model is better than the pre-trained CNN architecture and has a testing accuracy of over 97% in their ROC-AUC and classification metrics. The findings confirm the effectiveness of the hybrid scheme to achieve reliable and early detection of the disease of rice leaves. The proposed system will be expanded to identify other diseases of rice and multi-crop leaf and trained on the larger and more diverse datasets, which are taken in real field conditions, in future work. The combination of explainable AI methods will be considered to increase the transparency of models and user confidence. In addition, the framework will be evolved into a smart decision-support system that will offer disease-specific treatment advice and prevention. The ability to deploy on mobile and edge computing will allow real-time diagnosis of diseases and will be used to create sustainable, precision-driven agriculture.

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