

Machine Learning Approach for Detection of Diseased Rice Leaves Using a Convolutional Neural Network Architecture

Subrata Sinha, Saurav Mali, Mridul Bhuyan, Amit Kumar Pathak

Received 10 December 2025, Accepted 12 March 2026, Published on 24 March 2026

ABSTRACT

Rice (*Oryza sativa*) stands as a major staple crop extensively consumed not only in India but also globally. However, its production is affected by many biotic and abiotic factors. Infestations by various bacterial and viral pests is responsible for hampering the overall production of rice crops. Early detection of the diseased plants is a necessity to increase the overall production and improve the quality of rice crops. Hence automatic identification of diseased rice crop can assist the farmers for better care of the crop. The application of a deep learning approach utilizing the

Convolutional Neural Network (CNN) algorithm has proven highly effective in the detection of diseases from images of rice leaves. In this approach, a model has been developed, employing a Convolutional Neural Network architecture, to achieve accurate detection of diseased rice plants. The model was trained on a dataset of 2993 images, divided into 6 classes, out of which 5 classes are of various rice leaf diseases. It achieved an accuracy of 96%.

Keywords Machine learning, CNN, Artificial intelligence, Rice leaf diseases.

INTRODUCTION

Rice (*Oryza sativa*) is a staple food crop that is consumed by more than half of the global population. Rice is cultivated on over 163 million hectares of land in more than 100 countries, with a global production of approximately 500 million tons in 2020 (FAO 2021). The largest producers of rice are China, India, Indonesia, Bangladesh, and Vietnam (FAO 2021). In the Indian economic sector, agriculture plays an important role and contributes a second place in rice production. Rice is produced approximately in all the states of India (Krishnamoorthy *et al.* 2021). Rice is a unique crop in several aspects. It is one of the most

Subrata Sinha¹, Saurav Mali^{2*}, Mridul Bhuyan³, Amit Kumar Pathak⁴

¹Professor, ²Project Technical Support-III
Department of Computational Sciences, Brainware University,
Kolkata 700125, India

³Centre for Biotechnology and Bioinformatics, Dibrugarh
University, Dibrugarh 786004, Assam, India

⁴Project Associate
Chemical Sciences and Technology Division, CSIR-North East
Institute of Science and Technology, Jorhat 785006, Assam, India

Email: sm.2025,research@gmail.com

*Corresponding author

water-intensive crops, requiring large amounts of water for optimal growth and yield (Mallareddy *et al.* 2023). Rice is also a heavy feeder, requiring significant amounts of nutrients, particularly nitrogen, for optimal growth and yield (Wang and Peng 2017). The production of rice faces constraints imposed by both abiotic and biotic stresses, with insect pests contributing to approximately 25% of the losses, equivalent to around Rs. 240 billion, nearly 30 billion USD (Dhalwal *et al.* 2010). Over 100 insect species pose threats to rice crops throughout their growth stages, including nursery, maturity, and storage. While the majority of these species inflict relatively minor damage, tropical Asia experiences the regular occurrence of approximately 20 insect species of significant importance. These insects contribute to direct damage through ingestion or act as vectors for diseases (Heinrichs and Muniappan 2017) For instance, bacterial blight, caused by the bacterium *Xanthomonas oryzae* pv. *oryzae*, can cause yield losses of up to 50% in susceptible varieties (Liu *et al.* 2014). Similarly, various types of diseases can manifest in individual rice crops, posing a challenge for farmers to accurately identify them due to their limited knowledge acquired through practical experience (Krishnamoorthy *et al.* 2021). Manual detection of the diseased rice plants may take a long time and will hamper the overall production of the crop. It will ultimately lead to production loss, hampering economic growth in many counties, which are dependent on rice.

In recent times, computer vision techniques leveraging artificial intelligence, specifically Convolutional Neural Networks (CNNs), have been applied for the automated detection of diseases in diverse crops, showcasing encouraging outcomes. Lately, deep learning models have been utilized for the automated recognition and diagnosis of different diseases affecting rice plants. Convolutional Neural Network or CNN is a multi-layered neural network, that mimics the visual system of living beings. CNN is an algorithm of deep learning, which can efficiently process graphics data (Jianxin 2017). The CNN deep learning system is capable of processing visual data in an effective manner. image classification, image identification, graphics-data analysis, and other picturing difficulties are among the many applications for it. It is a forward-propagating artificial neural network

featuring three distinct layers: the input layer, hidden layer, and output layer. The hidden layer comprises a convolutional layer, pooling layer, normalization layer, and fully connected layer, incorporating a set of trainable parameters (weights). These parameters enable the network to learn the spatial relationships within the input data and execute a classification task (Krishnamoorthy *et al.* 2021). The output layer and the FC (completely connected) layer are the final two layers of a standard CNN model. After receiving the output from the final pooling layer, the FC layer produces a final output that is then processed further and provided by the output layer. (Gao *et al.* 2020, Mazzia *et al.* 2019, Kerdegari *et al.* 2019).

In our work, we have made an attempt to develop a CNN model, that can correctly predict and classify the different types of diseased rice leaf images. In due course of developing the machine learning model, we have incorporated various hyperparameter optimization techniques, to gain a deeper understanding of how these different optimization techniques affect the image classification tasks. The model which performed the best in the classification task was then converted into a TFLITE model and was integrated with an android based mobile application. Facilitating real world testing scenarios. The principal focal points of our study are outlined as follows:

We have introduced a novel machine learning model employing a Convolutional Neural Network (CNN) architecture. This model demonstrates enhanced accuracy in classifying images of diseased rice leaves and healthy rice leaves compared to previously developed models.

In our study, we have seamlessly integrated a machine learning model into an Android mobile application leveraging artificial intelligence, with the aim of delivering practical utility to farmers.

Related work

Since the last decade, a lot of research has taken place in the field of AI, to develop an optimal image classification model, that can aid in detection of diseased plant leaves. The automation of detecting the diseased plant provides the farmers with a quick definitive

plan, to tackle the production loss. In this section we shall be discussing some of the works that have been carried out by the researchers in the field of AI for detection and diagnosis of plant leaves diseases by using machine learning.

In the year 2015, Suman and Dhruvakumar (2015) developed an SVM classifier for the categorization of four distinct rice diseases: Bacterial Leaf Blight, Brown Spot, Narrow Brown Spot, and Rice Blast. Their study encompassed 60 samples, utilizing 10 features for the training of each disease and 5 samples for testing. The SVM classifier achieved a commendable accuracy level of 70% (Suman and Dhruvakumar 2015).

In the year 2017, another group of researchers proposed a CNN model which was able to classify 10 common rice diseases. They created a database of rice disease images, consisting of 500 images of 10 common rice diseases, including rice blast, rice false smut, rice brown spot, rice bakanae disease, rice sheath blight, rice sheath rot, rice bacterial leaf blight, rice bacterial sheath rot, rice seeding blight, and rice bacterial wilt. The size of the images was compressed to 512×512 . On comparing the results, the convolutional neural network (CNN) achieved the highest accuracy rate of 95%, followed by backpropagation (BP) at 92%, support vector machine (SVM) at 91%, and particle swarm optimization (PSO) at 88% (Lu *et al.* 2017).

In their study, Ahmed *et al.* (2019), developed a rice leaf disease detection system using machine learning techniques to identify three common diseases: leaf smut, bacterial leaf blight, and brown spot. The dataset was manually created, consisting of 120 images (40 for each disease class), which underwent pre-processing before being trained on different machine learning algorithms such as KNN, Decision Tree, Naive Bayes, and Logistic Regression. After 10-fold cross-validation, the Decision Tree algorithm achieved the highest accuracy of over 97% on the test dataset. (Ahmed *et al.* 2019). Parallely, Shrivastava and his colleagues developed a machine learning model for detecting and classifying plant diseases using images of diseased symptoms in rice leaves and stems. A total of 619 rice plant diseased

images were collected from the field, which were categorized into four classes: Rice Blast, Bacterial Leaf Blight, Sheath Blight, and Healthy Leaves. They used a pre-trained deep convolutional neural network as a feature extractor and Support Vector Machine as a classifier. They achieved a classification accuracy of 91.37% with a training-testing partition of 80%-20% (Shrivastava *et al.* 2019). Duong-Trung *et al.* (2019), used the transfer learning approach to train an Inception model to classify rice grain based on their discoloration. In their experiment, the researchers varied the necessary model parameters for their study, the learning rate was varied to 0.1, 0.01, and 0.001 respectively, and the model was trained for 1000, 3000, 6000, and 9000 no of epochs respectively. The model was trained using a dataset of grain discoloration that was randomly divided into a training set, a validation set, and a test set using an 80/10/10 split and was able to achieve a classification accuracy of 88% (Duong-Trung *et al.* 2019).

Chen *et al.* (2020) proposed a method to improve the learning ability of deep convolutional neural networks (CNNs) for detecting tiny lesion features in rice plant diseases. The model was trained on images that were collected from the experimental field of the agricultural scientific innovation base, Fujian Institute of Subtropical Botany, Xiamen, China. They used transfer learning by combining the Inception module and the pre-trained DenseNet on ImageNet for the target dataset. The top layers of the DenseNet were truncated and a new Inception module was defined with a fully-connected ReLU layer of 512 neurons and a fully-connected Softmax layer with the practical number of categories. They also utilized a Focal Loss function instead of the original Cross-Entropy Loss function to enhance the learning ability of the lesion features. The new network structure was named DENS-INCEP and tested on a dataset of 500 rice plant disease images. The proposed method achieved an average accuracy of 98.63% across all disease types. (Chen *et al.* 2020).

Yakkundimath *et al.* (2022), implemented transfer learning to develop deep learning models for classifying different disease diseases in rice plant. They used pre-trained VGG-16 and Google Net convolutional neural network (CNN) models and

evaluated their efficiency using a threefold cross-validation method on a held-out dataset. They used 12,000 labelled images of three different rice diseases for training and testing the models. The VGG-16 and Google Net models achieved an average classification accuracy of 92.24% and 91.28%, respectively. The results of their experiments demonstrated the practical usefulness of employing deep learning for rice plant disease classification (Yakkundimath *et al.* 2022). Elmitwally *et al.* (2022) proposed the AlexNet model for detecting three types of rice leaf diseases - Bacterial leaf blight, Brown spot, and Leaf smut. The dataset used in the study contained 120 photos of the three rice leaf diseases, divided into 80% training data and 20% test data. The AlexNet neural network was trained with a learning rate of 0.0001 and an epoch of 50, with validation conducted every three iterations. The proposed approach achieved a 99.0% accuracy rate for diagnosing rice leaf diseases (Elmitwally *et al.* 2022). Simultaneously, Purbasari *et al.* utilized Convolutional Neural Network (CNN) architecture to develop the model. The model was trained on a dataset consisting of 2,239 leaf images and was divided into training and testing set containing 2,071 and 168, respectively. The dataset had four types of leaf diseases, and the training size for each category ranged from 515 to 528. The CNN architecture used in the study comprised of two convolutional layers, two subsampling layers, and four fully connected layers. The study achieved a training accuracy of 91% (Purbasari *et al.* 2021). Temniranrat *et al.* (2021) proposed an automatic rice disease detection system integrated with a LINE Bot platform to diagnose rice diseases directly from paddy field images. Their approach utilized deep learning-based object detection models, with YOLOv3 selected as the deployment architecture after comparative evaluation against Faster R-CNN, RetinaNet, and Mask R-CNN. The training dataset was prepared from real field images captured without special sample preparation and annotated by plant pathology experts to ensure labeling accuracy. The model performance in the previous study achieved a mean Average Precision (mAP) of 79.19% (Temniranrat *et al.* 2021).

A research approach was proposed by Panchami and Vinod (2022) to diagnose five distinct types of rice diseases, namely Leaf Blast, Hispa, Tungro, Leaf

Blight, and Brown Spot. Their approach involved employing a sophisticated model designed to predict the specific disease type based on an uploaded or freshly captured image of the plant. The images underwent meticulous manual segmentation to eliminate background noise, and they were resized to dimensions of $224 \times 224 \times 3$ pixels. The model's performance was rigorously assessed using 200 samples from each disease class, resulting in an impressive overall accuracy rate of 93.33% (Panchami and Vinod 2022). Simultaneously, Tejaswini *et al.* (2022) undertook a parallel initiative, training a machine learning model with a dataset comprising 1600 images of rice leaves manifesting various disease classes. This dataset included 400 images of Brown Spot, 500 images of Hispa, 300 images of Leaf Blast, and 400 images of Healthy, all in high-resolution JPEG format with dimensions of 1449×1449 pixels. The study meticulously compared the performance of diverse machine learning and deep learning models, revealing that a 5-layer convolutional model emerged with the highest accuracy at 78.2%, surpassing other models such as VGG16, which exhibited a comparatively lower accuracy of 58.4% (Tejaswini *et al.* 2022).

In the year 2025, Ayyappan *et al.* (2025) developed a deep learning-based framework for rice plant disease detection using four CNN architectures—DenseNet121, EfficientNetB4, Xception, and MobileNetV3 Large. The models were trained on a dataset of 10,407 images covering 10 rice disease classes, including blast, brown spot, and bacterial blight. Among them, DenseNet121 achieved the highest accuracy of 97.5%, outperforming the others while EfficientNetB4 and MobileNetV3 Large achieved 96.25%, demonstrating strong potential for automated rice disease identification (Ayyappan *et al.* 2025). Verma *et al.* (2025) proposed a hybrid CNN framework integrating AlexNet, ResNet50, and EfficientNet-b1 architectures for rice variety classification. The dataset comprised 75,000 images from five rice varieties, and EfficientNet-b1 achieved the highest accuracy of 99.87%, outperforming the other models. The hybrid model demonstrated superior generalization and computational efficiency (Verma *et al.* 2025).

In the above cited work, most of the developed

models were trained with low a set of images and were trained on a pre trained CNN based architectures. Further, none of the developed models have not been deployed, neither as a mobile application nor as a web application.

In our work, we have made an attempt to develop a CNN- architecture based machine learning model, which was trained on an optimal dataset containing 2993 images. Further, we have also integrated our machine learning model with an android based mobile application.

MATERIALS AND METHODS

In the following section, we shall be discussing about the steps and techniques that we have implemented in developing our model. The section has been categorized into 6 segments.

Dataset acquisition

The proposed model has been trained with a total of 2993 images, displayed in Fig. 1 containing six different classes of rice leaves. These images included Bacterial Leaf Blight (499), Brown Spot (500),

Healthy (500), Hisa (500), Leaf Smut (494) and Leaf Blast (500), total of 5 diseased classes and 1 healthy class was used in training the proposed model. The said dataset has been downloaded from an online repository, Kaggle.

Proposed CNN architecture

In Fig. 2, the CNN model used for this study had 5 convolutional layers, 5 maxpool layers, 1flatten layer, 1 fully connected layer, and 1 output layer. The layer design followed a schema of [{1 Conv x 1 Max Pool} * 5+ 1Flatten + 1 FC + 1 Output]. During training, 80% of the images were used for training, 10% for testing, and 10% for validation. The kernel size used was 3x3, which performs convolution on the input image through element-by-element matrix multiplication. The resulting outcome is recorded in the feature map for each receptive field. To reduce the feature map's size, pooling layers were added after the convolutional layers to accommodate computational memory. Following numerous convolutional and pooling layers, 1 fully connected layer was added (To reduce the amount of human supervision required) to connect neurons between two different layers using weights, biases, and neurons. The flattened vector of the input image is then processed through those

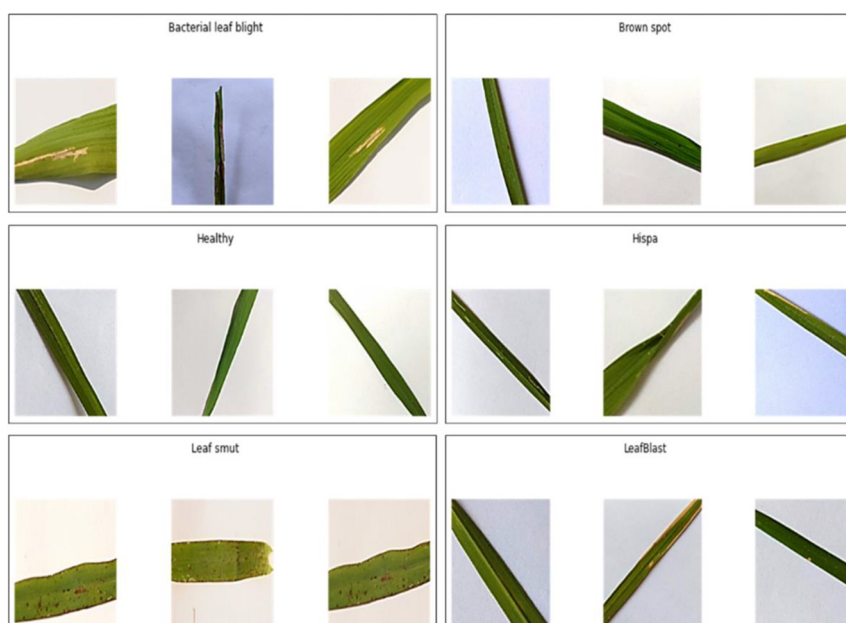


Fig. 1. Classes of Rice leaves obtained from Kaggle.

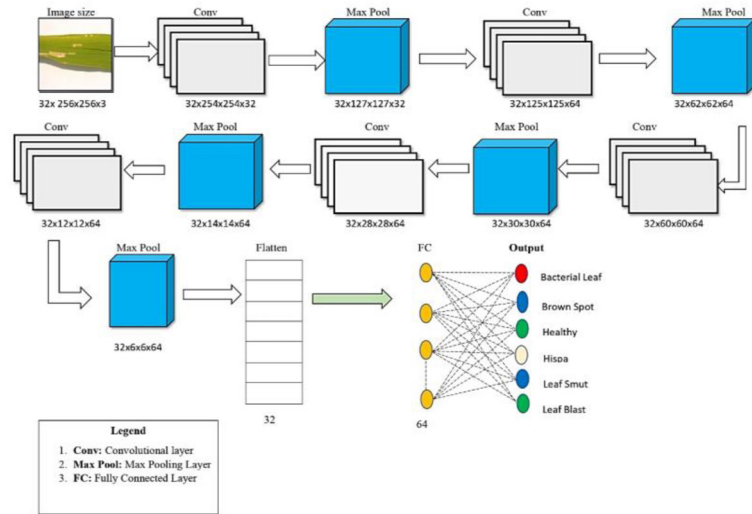


Fig. 2. Architecture of Proposed CNN Architecture.

fully connected layers, where standard mathematical operations occur to initiate the classification process. Finally, the SoftMax activation function was applied to the output layer to determine which model inputs should fire in the forward direction and which ones should not.

Proposed rice disease classification model

The dataset containing 6 classes of rice leaf images was embedded into the proposed CNN model. The model underwent training on a dataset segregated into five classes containing images of diseased rice leaves and one class comprising images of healthy rice leaves. The model was trained on the dataset which was divided into 5 classes of diseased rice leaf

images and 1 class of healthy rice leaf images. The dataset was divided into training set (80%) denoted as X_{train} , test set (10%) denoted as X_{test} and validation set (10%) denoted as X_{val} . We have performed data augmentation by means of random flipping and rotation, to increase the size and diversity of the dataset, which shall help the model to generalize better to new and unseen data. Furthermore, various hyper parameters such as number of epochs E , learning rate η , batch size b , were varied and configured accordingly, presented in Table 1. The model underwent training using three diverse optimizers: the Adaptive Moment Estimation algorithm (ADAM), Stochastic Gradient Descent (SGD), and Root Mean Square Propagation (RMSprop), with the objective of optimizing and improving its overall performance.

Table 1. Model Summary.

Model No	Optimizer	CNN layer	Epochs	Learning rate (η)	Batch-size b	Activation function f(x)
01	ADAM	12	100	0.1	32	ReLU
02	SGD	12	100	0.01	32	ReLU
03	RMSprop	12	100	0.001	32	ReLU
04	ADAM	12	100	0.1	32	ReLU
05	SGD	12	100	0.01	32	ReLU
06	RMSprop	12	100	0.001	32	ReLU
07	ADAM	12	100	0.1	32	ReLU
08	SGD	12	100	0.01	32	ReLU
09	RMSprop	12	100	0.001	32	ReLU

Table 2. Partition of the rice leaf images into training, validation and testing set.

Class	Partition of the dataset			
	Total images	Training (80%)	Validation (10%)	Testing (10%)
Bacterial Leaf Blight	499	399	50	50
Brown Spot	500	400	50	50
Healthy	500	400	50	50
Hisa	500	400	50	50
Leaf Smut	494	395	49	49
Leaf Blast	500	400	50	50

Development and deployment of the android mobile application

A total of 9 models were developed. Upon evaluation, the CNN model, which showed the highest accuracy and precision in classifying the different rice leaf classes, was then integrated with an Android application, which we built for real-time evaluation of the CNN model. The CNN model was converted to the TensorFlow-lite model, which was then integrated with the Android application to test the model in the real environment. The Android application was coded on Android Studio IDE, chipmunk version. The application was coded using Java 1.8. The application is supported on Android smartphones having Android version 6.0 or more. The Android Application named “RICE-SCN” is made available in google play-store, and can be downloaded and utilized by the users. The application can read images directly from the image gallery by the browse button, and it can also click real-time pictures from the application itself by clicking the button that opens the smartphone camera.

The initial testing was successful and yielded positive result in correctly classifying the different classes of diseased images and also differentiated the healthy set of images.

Model cross validation and evaluation criteria

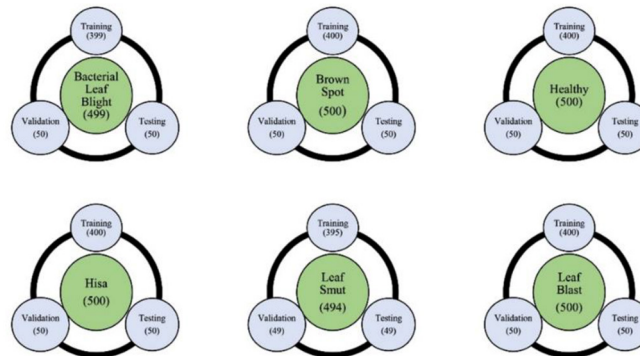
To ensure thorough cross-validation and assess the model’s performance, we have divided the dataset into 3 parts, training (80%), testing (10%) and validation (10%). Class wise partition of images has been presented in Table 2 and in Fig. 3. The step is followed when the dataset is very large. The training dataset was employed for model training, and the validation set served to evaluate the model’s performance at each epoch throughout the training process. Subsequently, the test dataset was utilized for model evaluation. Assessment metrics included sensitivity, specificity, precision, recall, F1-score, and Matthews Correlation Coefficient (MCC), while overall model performance was summarized using accuracy. The equations for the assessment metrics have been presented below from equation 1 to 7. Mean Average Precision was observed to evaluate the performance of the proposed model, presented in equation 8.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{Specificity} = \frac{TN}{TM + FP} \quad (4)$$

**Fig. 3.** Detailed description of the employed dataset containing 6 classes.

$$\text{F1-Score} = \frac{2\text{TP}}{2\text{TP} + \text{FN} + \text{FP}} \quad (5)$$

$$\text{(Negative Predictive Value) NPV} = \frac{\text{TN}}{\text{TN} + \text{FN}} \quad (6)$$

$$\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}} \quad (7)$$

TP (True Positives) denotes the count of instances accurately predicted as belonging to the positive class.

TN (True Negatives) signifies the count of instances accurately predicted as belonging to the negative class.

FP (False Positives) indicates the count of instances that actually belong to the negative class but were inaccurately predicted as the positive class.

FN (False Negatives) reflects the count of instances that actually belong to the positive class but were inaccurately predicted as the negative class.

$$\text{mAP} = \frac{1}{C} \sum_{i=1}^c \text{AP}_i \quad (8)$$

Where mAP: represents Mean Average Precision

C: denotes the total number of classes.

AP_i : denotes Average precision of each class.

Experimental setup

Our proposed model has been trained with a total of 2993 images, divided into 5 classes of diseased rice leaf images and 1 class of healthy rice leaf images. Data augmentation was performed by means of random flipping and rotation. Then the dataset was divided into 3 categories, training dataset consisted of about 80% of the images, which was used to train our model. The validation and testing dataset consisted of 10% each of the overall dataset. The validation dataset played a crucial role in monitoring our model's performance at each epoch, while the testing dataset served as the means to assess the overall performance of our proposed model. We employed different optimization algorithms to minimize the loss, each with varying learning rates: Adam, SGD, and RMSprop optimizers with learning rates of 0.1, 0.01, and 0.001, respective-

ly. Additionally, we fine-tuned multiple parameters, encompassing the establishment of a learning rate at 0.001, execution of 100 epochs, and adoption of a batch size of 32. Within the model architecture, the Rectified Linear Unit (ReLU) activation function was implemented in the hidden layers, whereas the Softmax activation function was employed in the output layer.

The Google Collab setup (GPUNvidia K80/T4, GPU Memory: 12 GB) was used to carry out our experiments. Python 3.9 was required for all experiments, and the CNN model was built with Tensorflow v2.12 as the back end and Keras Framework v2.11.0 as a high-level API. To get consistent findings, the experiments were run several times with each model. The outcomes of every study were tabulated and plotted.

RESULT AND DISCUSSION

Classification curves for the proposed models

In Fig. 4 (a-i), among the three optimizers employed, the Adam optimizer yielded the most favorable outcome, as evidenced by the minimal disparity observed between the training and validation accuracy. This alignment was further reflected in the congruence between the training and validation loss curves, indicating an absence of overfitting. Conversely, deployment of the SGD and RMSProp optimizers during model training resulted in overfitting, potentially compromising the model's ability to accurately classify unseen datasets.

Furthermore, the utilization of learning rates of 0.1 and 0.01 during model training failed to elicit improvements in both accuracy and loss rates. This absence of discernible enhancement suggests a potential under training of the model under these specific learning rates.

Confusion matrix of the proposed models

Evaluation metrics tables of the proposed models

Table 3 presents a comprehensive study of the attained performances employing the ADAM optimizer. The model in contemplation underwent training across

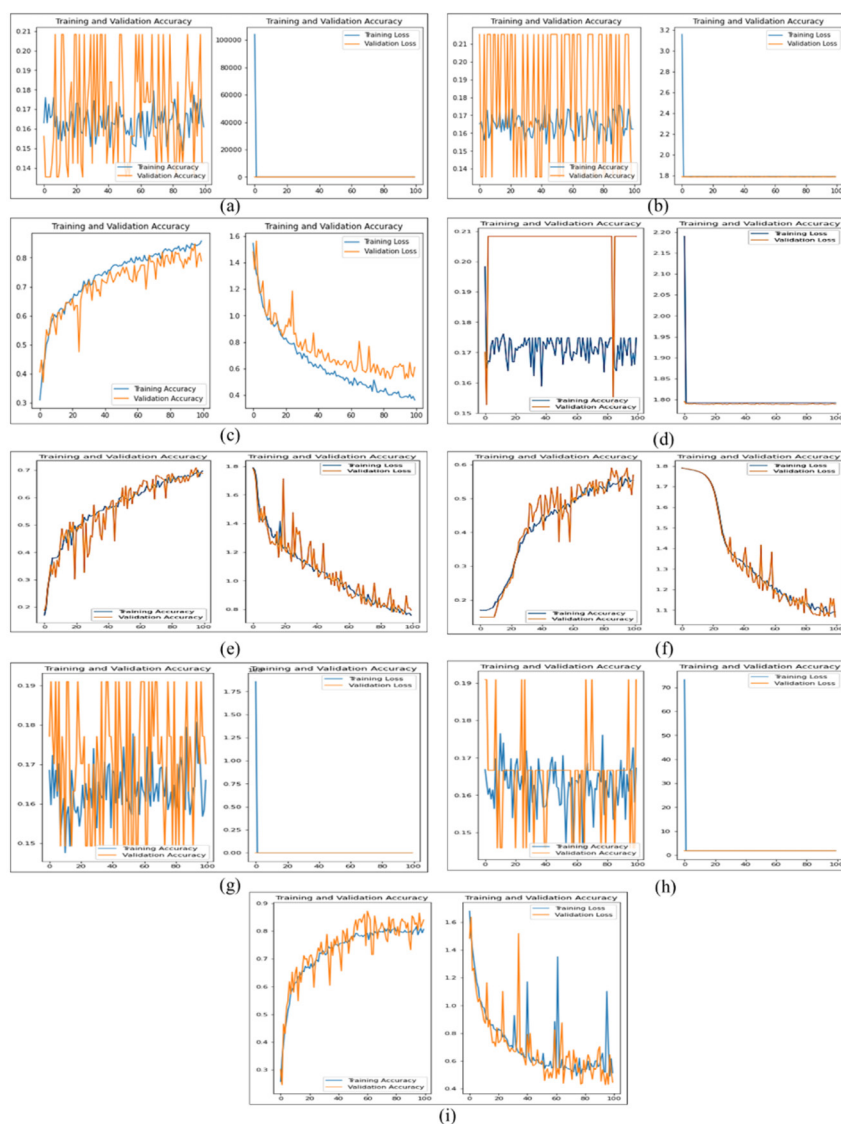


Fig. 4. Classification Curves (a) Adam optimizer at learning rate 0.1 (b) Adam optimizer at learning rate 0.01 (c) Adam optimizer at learning rate 0.001 (d) SGD optimizer at learning rate 0.1 (e) SGD optimizer at learning rate 0.01 (f) SGD optimizer at learning rate 0.001 (g) RMSprop optimizer at learning rate 0.1 (h) RMSprop optimizer at learning rate 0.01 (i) RMSprop optimizer at learning rate 0.001

three discrete learning rates: 0.1, 0.01, and 0.001. Leveraging the elucidated confusion matrix in Figure 5(a-c), a meticulous computation of model assessment metrics ensued, encompassing Accuracy, Precision, Sensitivity, Specificity, F1-Score, NPV, and MCC. These metrics derived from True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) values for each class—namely, Bacterial

Leaf Blight, Brown Spot, Healthy, Hisa, Leaf Smut, and Leaf Blasts. Foremost among these evaluations, the model's zenith performance materialized when subjected to a learning rate of 0.001. At this juncture, the model demonstrated an overarching accuracy of 96.67%, precision attaining 89.73%, sensitivity registering at 89.55%, and specificity impressively reaching 98.01%. Additionally, the model yielded

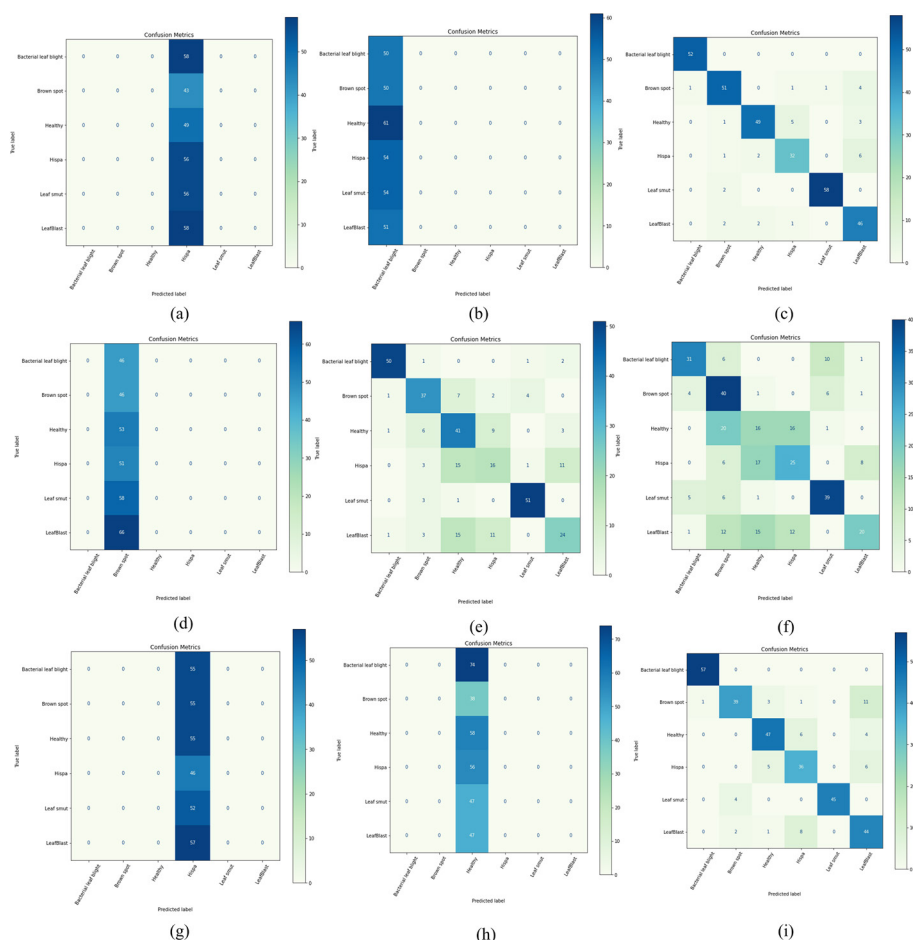


Fig. 5. Confusion Matrices (a) Adam optimizer at learning rate 0.1 (b) Adam optimizer at learning rate 0.01 (c) Adam optimizer at learning rate 0.001 (d) SGD optimizer at learning rate 0.1 (e) SGD optimizer at learning rate 0.01 (f) SGD optimizer at learning rate 0.001 (g) RMSprop optimizer at learning rate 0.1 (h) RMSprop optimizer at learning rate 0.01 (i) RMSprop optimizer at learning rate 0.001

markedly superior F1-Score (%), NPV (%), and MCC (%) values. Notably, within the spectrum of diverse learning rates employed during model training with the ADAM optimizer, the most favorable outcome transpired at a learning rate of 0.0001.

Conversely, the model's efficacy diminished notably when trained with learning rates of 0.1 and 0.01. In these instances, the desired accuracy remained elusive, accompanied by a conspicuous deterioration in various performance metrics. Importantly, the model exhibited a propensity for misclassification within distinct classes of rice leaf diseases under these suboptimal learning rates.

Within Table 4, the envisaged model underwent training with the Stochastic Gradient Descent (SGD) optimizer, adopting learning rates of 0.1, 0.01, and 0.001, respectively. Leveraging the insights derived from the elucidated confusion matrix in Fig. 5 (d-f), a comprehensive suite of model assessment metrics—namely, Accuracy, Precision, Sensitivity, Specificity, F1-Score, Negative Predictive Value (NPV), and Matthews Correlation Coefficient (MCC)—was meticulously computed. This rigorous analysis drew upon the interplay of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) values, uniquely assigned to each class (Bacterial Leaf Blight, Brown Spot, Healthy, Hisa, Leaf Smut,

Table 3. Proposed Model performance on original datasets with Adam optimizer with different learning rates.

Model	Learning rate	Optimizer	Class	Assessment Metrics						
				Acc (%)	Pr (%)	Sn (%)	Sp (%)	F1-S (%)	NPV (%)	MCC(%)
Proposed Model	0.1	Adam	Bacterial leaf blight	81.88	∞	0.00	100.00	0.00	81.88	∞
			Brown spot	86.56	∞	0.00	100.00	0.00	86.56	∞
			Healthy	84.69	∞	0.00	100.00	0.00	84.69	∞
			Hispa	17.50	17.50	100.00	0.00	29.79	∞	∞
			Leaf smut	82.50	∞	0.00	100.00	0.00	82.50	∞
			Leaf blast	81.88	∞	0.00	100.00	0.00	81.88	∞
			Overall	72.50	∞	16.67	83.33	4.96	∞	∞
Proposed Model	0.01	Adam	Bacterial leaf blight	15.63	15.63	100.00	0.00	27.03	∞	∞
			Brown spot	84.38	∞	0.00	100.00	0.00	84.38	∞
			Healthy	80.94	∞	0.00	100.00	0.00	80.94	∞
			Hispa	83.13	∞	0.00	100.00	0.00	83.13	∞
			Leaf smut	83.13	∞	0.00	100.00	0.00	83.13	∞
			Leaf blast	84.06	∞	0.00	100.00	0.00	84.06	∞
			Overall	71.88	∞	16.67	83.33	4.50	∞	∞
Proposed Model	0.001	Adam	Bacterial leaf blight	99.69	98.11	100.00	99.63	99.05	100.00	98.87
			Brown spot	95.94	89.47	87.93	97.71	88.70	97.34	86.22
			Healthy	95.94	92.45	84.48	98.47	88.29	96.63	85.96
			Hispa	95.00	82.05	78.05	97.49	80.00	96.80	77.18
			Leaf smut	99.06	98.31	96.67	99.62	97.48	99.23	96.91
			Leaf blast	94.38	77.97	90.20	95.17	83.64	98.08	80.57
			Overall	96.67	89.73	89.55	98.01	89.52	98.01	87.62

Table 4. Proposed Model performance on original datasets with SGD optimizer with different learning rates.

Model	Learning	Optimizer	Class	Assessment Metrics						
				Acc (%)	Pr (%)	Sn (%)	Sp (%)	F1-S (%)	NPV (%)	MCC(%)
Proposed Model	0.1	SGD	Bacterial leaf blight	85.63	∞	0.00	100.00	0.00	85.63	∞
			Brown spot	14.38	∞	100.00	0.00	25.14	∞	∞
			Healthy	83.44	∞	0.00	100.00	0.00	83.44	∞
			Hispa	84.06	∞	0.00	100.00	0.00	84.06	∞
			Leaf smut	81.88	∞	0.00	100.00	0.00	81.88	∞
			Leaf blast	79.38	∞	0.00	100.00	0.00	79.38	∞
			Overall	71.46	∞	16.67	83.33	4.19	∞	∞
Proposed Model	0.01	SGD	Bacterial leaf blight	97.81	94.34	92.59	98.87	93.46	98.50	92.15
			Brown spot	90.63	69.81	72.55	94.05	71.15	94.76	65.58
			Healthy	82.19	51.90	68.33	85.38	58.99	92.12	48.63
			Hispa	83.75	42.11	34.78	91.97	38.10	89.36	29.01
			Leaf smut	96.88	89.47	92.73	97.74	91.07	98.48	89.20
			Leaf blast	85.63	60.00	44.44	93.98	51.06	89.29	43.52
			Overall	89.48	67.94	67.57	93.67	67.31	93.75	61.35
Proposed Model	0.001	SGD	Bacterial leaf blight	91.56	75.61	64.58	96.32	69.66	93.91	65.07
			Brown spot	80.63	44.44	76.92	81.34	56.34	94.78	47.81
			Healthy	77.81	32.00	30.19	87.27	31.07	86.30	17.87
			Hispa	81.56	47.17	44.64	89.39	45.87	88.39	34.79
			Leaf smut	90.94	69.64	76.47	93.68	72.90	95.45	67.58
			Leaf blast	84.38	66.67	33.33	96.15	44.44	86.21	39.49
			Overall	84.48	55.92	54.36	90.69	53.38	90.84	45.43

Table 5. Proposed Model performance on original datasets with RMSprop optimizer with different learning rates.

Model	Learning rate	Optimizer	Class	Assessment Metrics						
				Acc (%)	Pr (%)	Sn (%)	Sp (%)	F1-S (%)	NPV (%)	MCC(%)
Proposed Model	0.1	RMSprop	Bacterial leaf blight	82.81	∞	0.00	100.00	0.00	82.81	∞
			Brown spot	82.81	∞	0.00	100.00	0.00	82.81	∞
			Healthy	82.81	∞	0.00	100.00	0.00	82.81	∞
			Hispa	14.38	∞	100.00	0.00	25.14	∞	∞
			Leaf smut	83.75	∞	0.00	100.00	0.00	83.75	∞
			Leaf blast	82.19	∞	0.00	100.00	0.00	82.19	∞
			Overall	71.46	∞	16.67	83.33	4.19	∞	∞
Proposed Model	0.01	RMSprop	Bacterial leaf blight	76.88	∞	0.00	100.00	0.00	76.88	∞
			Brown spot	88.13	∞	0.00	100.00	0.00	88.13	∞
			Healthy	18.13	18.13	100.00	0.00	30.69	∞	∞
			Hispa	82.50	∞	0.00	100.00	0.00	82.50	∞
			Leaf smut	85.31	∞	0.00	100.00	0.00	85.31	∞
			Leaf blast	85.31	∞	0.00	100.00	0.00	85.31	∞
			Overall	72.71	∞	16.67	83.33	5.11	∞	∞
Proposed Model	0.001	RMSprop	Bacterial leaf blight	80.96	98.28	43.51	99.62	60.32	77.98	57.35
			Brown spot	94.42	86.67	70.91	98.23	78.00	95.42	75.33
			Healthy	76.40	36.15	82.46	75.37	50.27	96.21	43.26
			Hispa	93.40	70.59	76.60	95.68	73.47	96.79	69.78
			Leaf smut	98.98	100.00	91.84	100.00	95.74	98.85	95.28
			Leaf blast	91.88	67.69	80.00	93.81	73.33	96.66	68.92
			Overall	89.34	76.56	74.22	93.78	71.86	93.65	68.32

and Leaf Blast), culminating in a holistic evaluation of the model's performance.

Of notable significance, the model trained with a learning rate of 0.01 demonstrated superior performance, excelling both in class-specific evaluations and overall metrics when trained with alternative learning rates. Specifically, the model achieved an overarching accuracy of 89.48%, coupled with a precision of 67.94%, sensitivity of 67.57%, and specificity of 93.67%. This commendable performance was further underscored by a notably enhanced NPV. Conversely, when employing a learning rate of 0.1, the proposed model encountered a notable deficiency, failing to effectively classify any instances within the diseased rice leaf classes, resulting in a markedly diminished accuracy.

Within Table 5, the developed model underwent a training regimen employing the RMSProp optimizer, with varying learning rates of 0.1, 0.01, and 0.001.

This tabular presentation meticulously delineates a class-specific scrutiny of the model across distinct learning rates, encapsulating an exhaustive evaluation of overall metrics. The elucidation of model performance, encompassing Accuracy, Precision, Sensitivity, Specificity, F1-Score, NPV, and MCC, calculated from a judicious analysis of the confusion matrix depicted in Fig. 5 (g-i). These metrics, derived from the interplay of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each class (Bacterial Leaf Blight, Brown Spot, Healthy, Hisa, Leaf Smut, and Leaf Blast), collectively contribute to a comprehensive assessment. Remarkably, the model trained with a learning rate of 0.001 demonstrated unparalleled efficacy in both class-specific and overarching evaluations.

Among all three optimizers for learning rate 0.001, ADAM demonstrated superior performance across all performance metrics, achieving a high accuracy rate in accurately classifying various rice diseases.

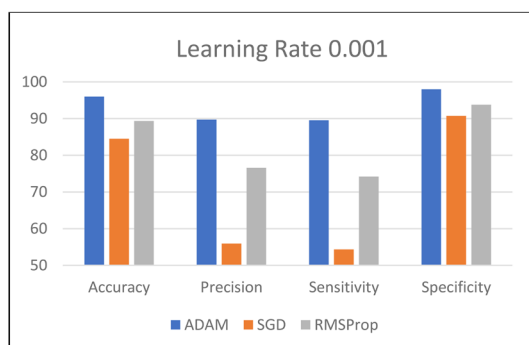


Fig 6. Comparative analysis of the model (Accuracy, Precision, Sensitivity, Specificity), with different optimizers.

In Fig 6, discernible disparities emerge as the model, meticulously trained with the Adam optimizer, attains markedly superior outcomes in accuracy, precision, specificity, and sensitivity relative to its counterparts—SGD and RMSProp optimizers. This commendable performance was achieved under the careful consideration of a learning rate set at 0.001.

Inferences drawn from Table 6 indicate that within the referenced models, our model, trained using

the Adam optimizer with a learning rate of 0.001, has exhibited the highest accuracy. This achievement is particularly noteworthy considering the extensive dataset comprising of 2993 rice leaf images. It is noteworthy that while the model developed by Lu *et al.* surpassed our model in accuracy, the superior performance may be attributed to a smaller dataset containing only 500 images, potentially resulting in under training due to its limited size.

Deployment of the machine learning model in an android based mobile application

The above Fig. 7 demonstrates the working of our mobile application. Here, we have integrated our best optimized model with an android based mobile application. Fig. 7 (a) overall displays the user interface of the developed application. On testing our developed model with various classes of diseased rice leaf images, the model was able to classify and predict the different classes of rice diseased images, with an optimal accuracy. Fig. 7(b) displays our model classifying the diseased image class of Bacterial Leaf Blight as ‘Bacterial Leaf Blight’ with an accuracy of 99.95%, whereas Fig. 7(c) displays our model classifying the diseased image class of Brown Spot

Table 6. Evaluation of the performance of our models in relation to the documented models in the literature.

Sl. No.	Author	Year	Model	Dataset (Total No. of Images)	Overall Accuracy (%)
1	Suman and Dhruvakumar	2015	SVM	60	70
2	Lu <i>et al.</i>	2017	CNN	500	95
3	Ahmed <i>et al.</i>	2019	Decision Tree	120	97
4	Shrivastava <i>et al.</i>	2019	CNN, SVM	619	91
5	Duong Tung <i>et al.</i>	2019	CNN	-	88
6	Chen <i>et al.</i>	2020	CNN model with transfer learning	500	98.30
7	Yakkundimath <i>et al.</i>	2022	CNN	12000	91
8	Purbasari <i>et al.</i>	2021	CNN	2239	91
9	Temniranrat <i>et al.</i>	2021	CNN	Not mentioned	79.19 (mAP)
10	Panchami and Vinod	2022	CNN architecture	800	90
11	Tejaswini <i>et al.</i>	2022	CNN	1600	78
Learning Rate of 0.001 is considered for the proposed models with different optimizers					
12	Proposed Model with ADAM optimization	2023	CNN architecture	2293	96
13	Proposed Model with SGD optimization	2023	CNN architecture	2293	68
14	Proposed Model with RMSprop optimization	2023	CNN architecture	2293	84

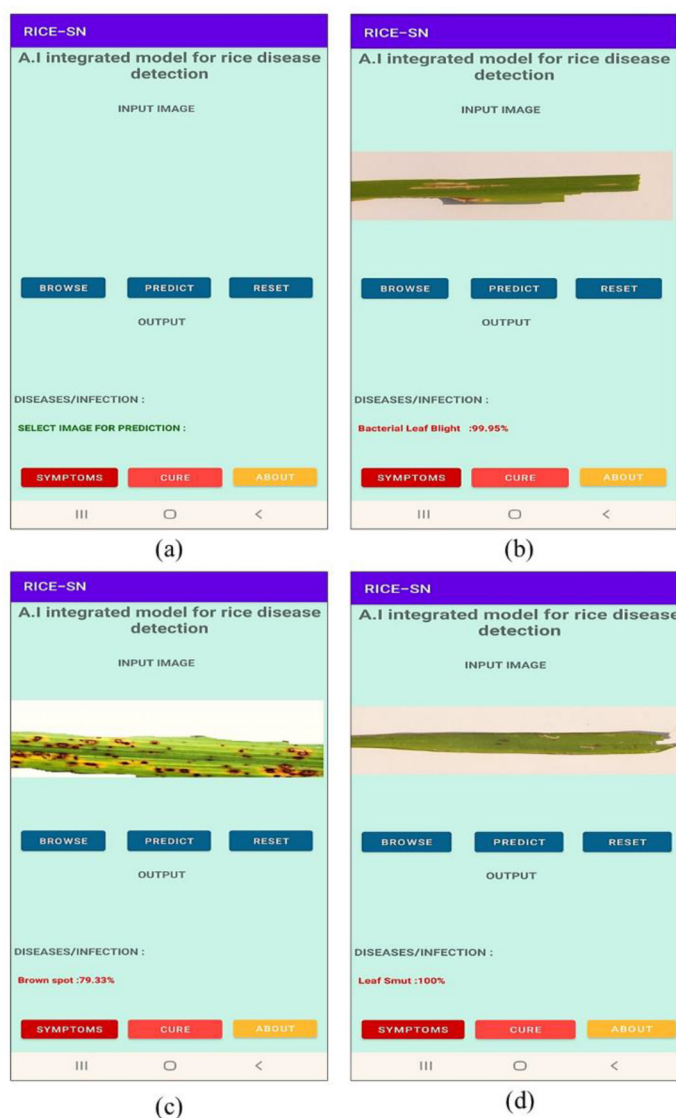


Fig. 7(a). Screenshot of the RICE-SCN **(b)** Bacterial Leaf Blight disease detection with an accuracy of 99.95% **(c)** Brown Spot disease detection with an accuracy of 79.33% **(d)** Leaf Smut disease detection with an accuracy of 100%.

as 'Brown Spot' with an accuracy of 79.33%. And finally, in Fig. 7 (d), the app was able to correctly classify Leaf Smut image as 'Leaf Smut', with an accuracy of 100%.

CONCLUSION

The timely identification and treatment of rice leaf diseases play a pivotal role in mitigating yield losses.

The integration of artificial intelligence (AI) into agricultural applications enhances the efficiency of disease detection, facilitating prompt and accurate diagnosis, thereby contributing to a more effective management of crop health.

In this study, multiple CNN models with 12-layer configurations were developed for rice disease classification using leaf images. The model trained with the

ADAM optimizer at a learning rate of 0.001 achieved the highest accuracy of 96.67%, outperforming other optimizer and learning-rate combinations. It effectively classified Bacterial Leaf Blight, Brown Spot, Leaf Smut, and healthy rice leaf images.

To improve accessibility for farmers, an AI-based Android application was developed to classify rice leaf diseases, identify healthy leaves, and distinguish leaf from non-leaf images. The proposed CNN models demonstrate reliable classification performance, supporting efficient rice disease diagnosis with potential benefits in yield optimization, loss reduction, and enhanced rice production.

ACKNOWLEDGMENT

The authors sincerely extend their heartfelt appreciation to the Department of Computational Sciences and the Centre for Multidisciplinary Research and Innovation at Brainware University, Barasat, West Bengal, for their invaluable institutional assistance during the preparation of the manuscript.

REFERENCES

- Ahmed, K., Shahidi, T. R., Alam, S. M. I., & Momen, S. (2019, December). Rice leaf disease detection using machine learning techniques. In International Conference on Sustainable Technologies for Industry 4.0 (STI) (pp. 1-5). IEEE.
- Ayyappan, A. B., Gobinath, T., Kumar, M., & Sivaramakrishnan, A. (2025). Rice Plant Disease Detection using Convolutional Neural Networks. *Discover Artificial Intelligence*, 5(1), 50.
- Chen, J., Zhang, D., & Nanekaran, Y. A. (2020). Identifying plant diseases using deep transfer learning and enhanced light-weight network. *Multimedia tools and applications*, 79, 31497-31515.
- Dhaliwal, G. S., Jindal, V., & Dhawan, A. K. (2010). Insect pest problems and crop losses: Changing trends. *Indian Journal of Ecology*, 37, 1-7.
- Duong-Trung, N., Quach, L. D., Nguyen, M. H., & Nguyen, C. N. (2019). Classification of grain discoloration via transfer learning and convolutional neural networks. In Proceedings of the International Conference on Machine Learning and Soft Computing, Da Lat, Vietnam, 25-28 January pp. 27-32.
- Elmitwally, N. S., Tariq, M., Khan, M. A., Ahmad, M., Abbas, S., & Alotaibi, F. M. (2022). Rice Leaves Disease Diagnose Empowered with Transfer Learning. *Computer Systems Science and Engineering*, 42(3), 1001-1014. <https://doi.org/10.32604/csse.2022.022017>
- Food and Agriculture Organization of the United Nations. (2021). FAOSTAT Database. Rome, Italy: FAO. Retrieved from <http://www.fao.org/faostat/en/home>
- Gao, J., French, A. P., Pound, M. P., He, Y., Pridmore, T. P., & Pieters, J. G. (2020). Deep convolutional neural networks for image-based *Convolvulus sepium* detection in sugar beet fields. *Plant Methods*, 16(1), 1-12.
- Heinrichs, E. A., & Muniappan, R. (2017). IPM for tropical crops: Rice. *CABI Rev.* 12, 1-31.
- Jianxin Wun (2017), Introduction to Convolutional Neural Networks, National Key Lab for Novel Software Technology Nanjing University, China.
- Kerdegari, H., Razaak, M., Argyriou, V., & Remagnino, P. (2019). Smart monitoring of crops using generative adversarial networks. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 11678 LNCS, 554-563. https://doi.org/10.1007/978-3-030-29888-3_45
- Krishnamoorthy, N., Narasimha Prasad, L. V., Pavan Kumar, C. S., Subedi, B., Baraki Abraha, H., & Sathishkumar, V. E. (2021). Rice leaf diseases prediction using deep neural networks with transfer learning. *Environmental Research*, 198, 111275. <https://doi.org/10.1016/j.envres.2021.111275>
- Liu, W., Liu, J., Triplett, L., Leach, J. E., & Wang, G. L. (2014). Novel insights into rice innate immunity against bacterial and fungal pathogens. *Annual Review of Phytopathology*, 52, 213-241.
- Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. *Neurocomputing*, 267, 378-384.
- Mallareddy, M., Thirumalaikumar, R., Balasubramanian, P., Naseeruddin, R., Nithya, N., Mariadoss, A., Eazhilkrishna, N., Choudhary, A. K., Deiveegan, M., Subramanian, E., Padmaja, B., & Vijayakumar, S. (2023). Maximizing Water Use Efficiency in Rice Farming: A Comprehensive Review of Innovative Irrigation Management Technologies. *Water*, 15(10), 1802. <https://doi.org/10.3390/w15101802> <https://doi.org/10.1146/annurev-phyto-102313-045926>
- Mazzia, V., Khaliq, A., & Chiaberge, M. (2019). Improvement in land cover and crop classification based on temporal features learning from Sentinel-2 data using recurrent convolutional Neural Network (R-CNN). *Applied Sciences*, 10(1), 238. <https://doi.org/10.3390/app10010238>
- Panchami, R., & Vinod, S. (2022). Rice Leaf Disease Detection and Diagnosis Using Convolution Neural Network. <https://doi.org/10.21203/rs.3.rs-1812823/v1>
- Purbasari, I. Y., Rahmat, B., & Putra PN, C. S. (2021). Detection of Rice Plant Diseases using Convolutional Neural Network. IOP Conference Series: *Materials Science and Engineering*, 1125(1), 012021. <https://doi.org/10.1088/1757-899x/1125/1/012021>
- Shrivastava, V. K., Pradhan, M. K., Minz, S., & Thakur, M. P. (2019). Rice Plant Disease Classification Using Transfer Learning Of Deep Convolution Neural Network. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-3/W6, 631-635. <https://doi.org/10.5194/isprs-archives-xlii-3-w6-631-2019>
- Suman, T., & Dhruvakumar, T. (2015). Classification of paddy leaf diseases using shape and color features. *International Journal of Electrical and Electronics Engineers*, 7(1), 239-250.
- Teja kattenborn, Jens Leitloff, Felix Schiefer, Stefan Hinz (2021). Review on Convolutional Neural Networks (CNN) in veg-

- etation remote sensing, *ISPRS Journal of Photogrammetry and Remote Sensing*, Volume 173, 24-49.
- Tejaswini, Pallapothala & Ramchandani, Monica & Rathore, Yogesh & Janghel, Rekh. (2022). Rice Leaf Disease Classification Using Cnn. IOP Conference Series: *Earth and Environmental Science*. 1032. 012017.
<https://doi.org/10.1088/1755-1315/1032/1/012017>
- Temniranrat, P., Kiratiratanapruk, K., Kitvimonrat, A., Sinthupinyo, W., & Patarapuwadol, S. (2021). A system for automatic rice disease detection from rice paddy images serviced via a Chatbot. *Computers and Electronics in Agriculture*, 185, 106156.
- Verma, D. S., Dafadar, M., Mishra, J. K., Kumar, A., & Mahato, S. (2025). AI-Enable Rice Image Classification Using Hybrid Convolutional Neural Network Models. *International Journal of Intelligent Systems*, 2025(1), 5571940.
- Wang, F., & Peng, S. (2017). Yield potential and nitrogen use efficiency of China's super rice. *Journal of Integrative Agriculture*, 16(5), 1000–1008.
- Yakkundimath, Rajesh & Saunshi, Girish & Anami, Basavaraj & Palaiah, & Surendra. (2022). Classification of Rice Diseases using Convolutional Neural Network Models. *Journal of The Institution of Engineers (India): Series B*. 103.
<https://doi.org/10.1007/s40031-021-00704-4>