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A novel approach to enhance rice foliar disease detection: custom data generators, advanced augmentation, hybrid fine-tuning, and regularization techniques with DenseNet121

Govindarajan Subburaman, Mary Vennila Selvadurai
Post Graduate and Research Department of Computer Science, Presidency College, University of Madras, Chennai, India

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ABSTRACT

Rice leaf diseases impact crop yield, leading to food shortages and economic losses. Early, automated detection is essential but often hindered by accuracy challenges. This study contributes to improving model robustness against diverse and adversarial inputs by proposing a custom data generator that applies Albumentation-based advanced augmentations, such as Gaussian blur, noise addition, brightness/contrast adjustments, and coarse dropout, to enhance model generalization. Five deep learning architectures—simple convolutional neural network (CNN), ResNet50, EfficientNetB0, Inception v3, and DenseNet121—were evaluated for classifying six categories: bacterial blight, brown spot, leaf blast, leaf scald, narrow brown spot, and healthy leaf. A hybrid model approach is proposed, fine-tuning the DenseNet121 model by unfreezing its last 20 layers, which balances transfer learning benefits with domain-specific feature extraction. Regularization techniques, including L2 regularization and a reduced dropout rate, are incorporated to control overfitting. Additionally, a custom learning rate scheduler is proposed to promote stable training. DenseNet121 achieved the highest performance, with an accuracy of 98.41%, demonstrating the effectiveness of these advanced augmentation and tuning strategies in rice leaf disease classification.

Corresponding Author:

Govindarajan Subburaman
Post Graduate and Research Department of Computer Science, Presidency College, University of Madras
Chennai, India
Email: thimagovind7@gmail.com

1. INTRODUCTION

Rice is a vital cereal grain that has significantly enhanced global food security over the past fifty years [1], [2]. The global agricultural sector is encountering major challenges as the demand for food production rises to support an expanding population [3]. One of the primary factors contributing to a significant decline in rice production is disease, which can cause a reduction in yield by 40%–50%, or even result in complete crop failure in severe cases [4]. Timely detection and identification of disease types are crucial for ensuring rice production. Diagnosis and prevention of common rice diseases typically rely on characteristic symptoms, requiring field expertise and experience. For non-experts, such as farmers who may not be familiar with the timing and symptoms of rice diseases, there is a high risk of misjudgment, low efficiency, and heavy reliance on experts. This often leads to delays in accurate disease management, resulting in reduced rice yields [5]. This research focused on utilizing data augmentation techniques to improve the classification of rice diseases. Data augmentation involves generating additional training samples by applying various transformations to existing data, which helps enhance model performance by increasing data diversity and reducing overfitting. This approach aims to address the challenge of limited data availability in rice disease classification, thereby improving the accuracy and robustness of the classification models.

Data augmentation techniques allow for an increase in the size of a dataset without the need to collect additional data. These techniques generate new data from the original training set by applying basic manipulations and advanced image transformations [6]. The most commonly used image manipulation techniques include flipping, cropping, rotation, color transformation, and noise injection. These methods can be applied individually or in combination to generate augmented images through various image formatting approaches [7]. However, the shortage of images of infected plant leaves has historically been a major obstacle to effective plant disease detection. Figure 1 illustrates some common widespread diseases.

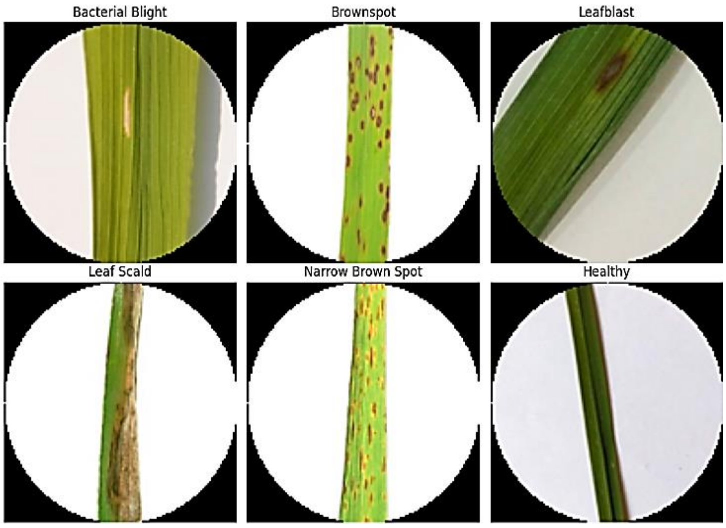


Figure 1. Common rice leaf diseases

The proposed advanced data augmentation method generates sufficient and high-quality rice leaf disease images, enhancing the diversity and robustness of the training data. This augmentation technique, applied dynamically via a custom data generator, significantly improves the performance of various deep learning models.

The key contributions of this paper can be outlined as follows.

a. Custom data generator with advanced augmentation: Instead of employing standard augmentation methods, the code leverages Albumentation, a versatile and efficient augmentation library that enables complex transformations. The custom data generator applies these augmentations dynamically during training, enhancing the model’s robustness and handling of diverse image conditions.
b. Hybrid model approach with fine-tuning: By unfreezing the last 20 layers of the DenseNet121 base model, the code fine-tunes the pretrained network to the specific rice leaf disease dataset. This approach balances the advantages of transfer learning with the need for domain-specific feature extraction, allowing the model to adapt more effectively to the nuances of the dataset.
c. Regularization and dropout adjustments: The integration of L2 regularization on the dense layer, combined with a lower dropout rate in the classification head, demonstrates a well-structured method to control overfitting. This adjustment is crucial given the complexity of DenseNet121 and the modest size of the dataset.
d. Custom learning rate scheduler: The use of a learning rate reduction callback, designed to reduce the learning rate more gradually and with a higher patience threshold, ensures training stability. This approach is particularly beneficial for deep networks like DenseNet121, promoting better convergence and performance over time.

2. RELATED WORKS

Data augmentation has been widely employed by many researchers in machine learning and deep learning approaches to enhance model performance, improve generalization, and address challenges related to limited or imbalanced datasets. Krishnamoorthy *et al.* [8] used original training dataset was expanded using image augmentation techniques such as rotation, vertical and horizontal flipping, shearing, and random zooming. These real-time augmentations were implemented using the image data generator class from the keras deep learning library. Haque *et al*. [9] labeled and uploaded images to platforms like Roboflow for augmentation to enhance the volume and diversity of the dataset. The primary objective of data augmentation was to mitigate overfitting, particularly in small datasets, by generating new images through techniques such as flipping, cropping, and altering color spaces. Qi *et al.* [10] focused on the automatic identification of groundnut leaf diseases using a stack ensemble approach. The research aimed to classify four types of groundnut leaf diseases by combining deep learning models with traditional machine learning techniques. Deep neural networks, specifically ResNet50 and DenseNet121, demonstrated superior performance in predicting the dataset. The highest accuracy achieved with data augmentation was 97.59%. Among the models, ResNet50 showed the best identification performance when combined with the logistic regression (LR) model. Salini *et al.* [11] reduce pesticide usage in agriculture while enhancing the quality and quantity of crop yields. Image processing techniques are utilized for feature extraction, and classification is performed using support vector machine (SVM). To further improve model performance and results, data augmentation is employed. Hasan *et al.* [12] focus to improve the identification and classification of diseases, utilizing enhanced methodologies can significantly reduce false classifications and optimize performance. Expanding the dataset with additional images through augmentation and fine-tuning the machine learning model's parameters can further boost classification accuracy. Liu *et al.* [13] used the dataset generated by Leaf GAN achieved a higher average recognition accuracy compared to traditional data augmentation techniques and other GAN-based methods. When tested on the Xception model, it resulted in an average test accuracy of 98.70%. This study applied an 8-fold rotation data augmentation [14] strategy, rotating each training image in 45° increments from 0° to 360°. Zhang *et al.* [15] achieved a recognition accuracy improvement of 4.57% with ResNet18 and 4.1% with VGG11 when compared to results without data augmentation. Additionally, when compared to the conventional WGAN-GP data augmentation technique, accuracy increased by 3.08% with ResNet18 and 3.55% with VGG11. Waheed *et al*. [16] implemented a DenseNet model that demonstrated impressive performance, achieving 98.06% accuracy in identifying three types of corn leaf diseases. The use of data augmentation techniques helped to increase the dataset size, thereby enhancing the model's generalization capabilities. A diverse set of plant leaf disease datasets was created [17] using a combination of basic image manipulation and advanced deep learning augmentation techniques, including image flipping, cropping, rotation, color transformation, principal component analysis (PCA) color augmentation, noise injection, GANs, and neural style transfer (NST). The effectiveness of these augmentation methods was evaluated with leading transfer learning models such as VGG16, ResNet, and Inception v3. A regularization technique was applied to classify rice diseases from leaf images with a limited dataset, yielding better results than a standard convolutional neural network (CNN) model, as demonstrated by an average accuracy rate of 85.878% [18]. Haruna *et al*. [19] trained StyleGAN2-ADA for 250 epochs, utilizing the variance of the Laplacian filter to eliminate blurry or poorly generated images. These synthesized images were then used to augment Faster R-CNN and species sensitivity distribution (SSD) models for detecting rice leaf diseases. Ritharson *et al*. [20] used models for experiment—Xception, DenseNet121, Inception-Resnet-v2, Inception v3, ResNet50, and VGG16—were selected based on their strong performance in various applications for data classification using pre-trained networks and weight decay (L2 regularization). To enhance prediction accuracy and mitigate overfitting with limited training data, Bi and Hu [21] proposed a Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) that was combined with Label Smoothing Regularization (LSR). The studies in [21]–[27] used three different architectures. DenseNet201 achieved an average accuracy of 89.86% on the non-normalized dataset, 88.33% on the normalized augmented dataset, and 83.41% on the non-normalized augmented dataset. GoogleNet recorded the lowest accuracy of 83.87% on the non-normalized dataset, while AlexNet had the lowest accuracies of 82.38% and 79.72% on the normalized and non-normalized augmented datasets, respectively.

3. PROPOSED METHODOLOGY

In the existing methodology, as illustrated in Figure 2, the dataset is first collected and split into training and test sets. Basic augmentation techniques, such as rotations, flips, and scaling, are applied to the training images to increase data variability. The augmented data is then fed into a model, which is trained to classify different rice leaf diseases. The model processes the images and categorizes them into predefined disease classes based on the features extracted during training.

The proposed methodology begins with data collection and preprocessing, where images of rice leaves from various disease categories are loaded and resized to ensure compatibility with the model's input. As shown in Figure 3, the dataset is divided into training, validation, and test sets, with the labels one-hot encoded for multi-class classification.

The rice leaf image dataset utilized in this research was obtained through the Kaggle API. In this study, the dataset comprises six categories, as depicted in Figure 1. The technique of advanced image augmentation was applied to increase the size of the original training dataset by creating variations of the existing images. In this research, several advanced augmentation techniques were explored, as detailed.

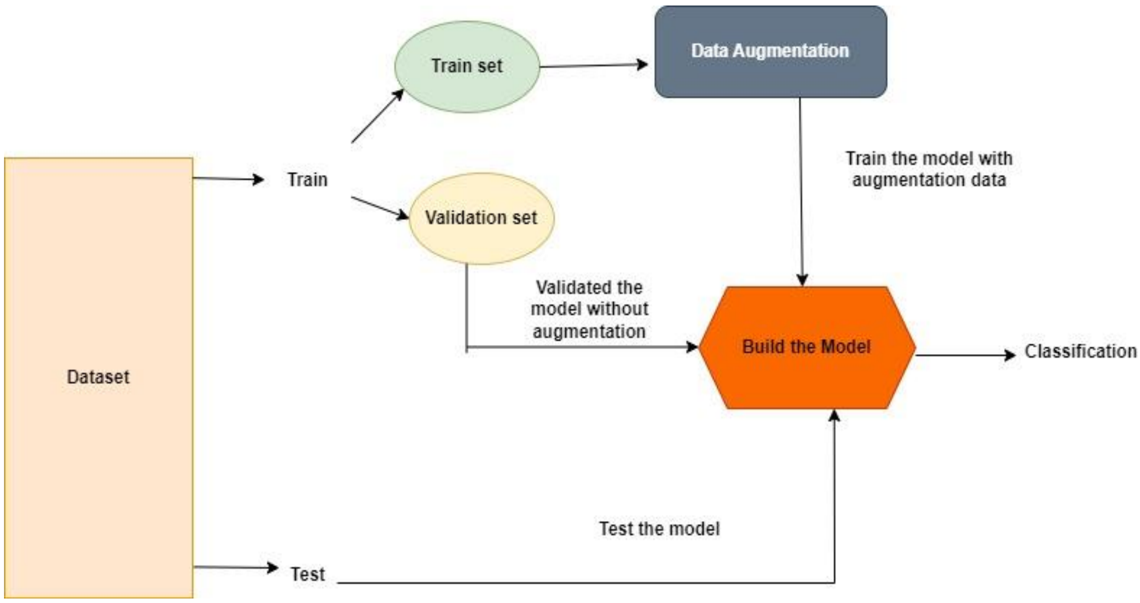


Figure 2. Existing systematic approach for identifying rice leaf diseases

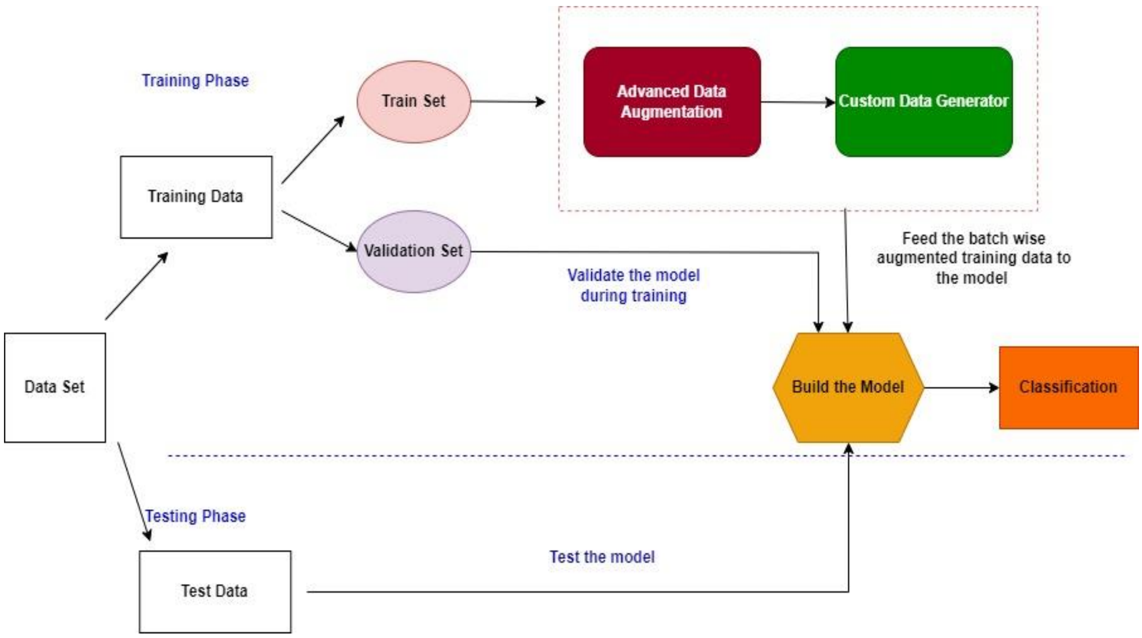


Figure 3. Proposed systematic approach for identifying rice leaf diseases

a. Random rotate 90: this rotates the image by multiples of 90 degrees. The transformation matrix for a 90-degree rotation counterclockwise is:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \tag{1}$$

b. Horizontal flip: reflects the image across the vertical axis. The transformation matrix is:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \quad (2)$$

c. Vertical flip: reflects the image across the horizontal axis. The transformation matrix is:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \quad (3)$$

d. Transpose: transpose operation swaps the x and y coordinates of the image:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \quad (4)$$

e. Gaussian blur: Gaussian blur applies a filter using a Gaussian function. This is represented as a convolution operation:

$$I'(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x - i, y - j) G(i, j) \quad (5)$$

where $G(i, j)$ is the Gaussian kernel defined as:

$$G(i, j) = \frac{1}{2\pi\sigma^2} e^{-\frac{i^2+j^2}{2\sigma^2}} \quad (6)$$

where σ controls the blur intensity.

f. Gauss noise: adds random noise to each pixel value. For a given pixel $I(x, y)$, the noise is added as:

$$I'(x, y) = I(x, y) + N(0, \sigma) \quad (7)$$

where $N(0, \sigma)$ is a Gaussian random variable with mean 0 and standard deviation σ controlling the noise level.

g. Random brightness contrast: this operation adjusts both brightness and contrast. Brightness: for each pixel $I(x, y)$, brightness adjustment is:

$$I'(x, y) = I(x, y) + \Delta B \quad (8)$$

where ΔB is the random brightness change factor. Contrast: for contrast adjustment:

$$I'(x, y) = (I(x, y) - 128).C + 128 \quad (9)$$

where C is a contrast factor, and 128 is the midpoint pixel value (for 8-bit images). CoarseDropout: coarse dropout randomly fills some patches of the image with a fixed value (usually black). For a patch (x_1, y_1) to (x_2, y_2), the (10) is:

$$I(x, y) = \text{fill\_value} \ \forall(x_1 \leq x \leq x_2, y_1 \leq y \leq y_2) \quad (10)$$

h. ShiftScaleRotate: this combines shifting, scaling, and rotating. Shift: for a shift by(t_x, t_y), the new pixel coordinates are:

$$x' = x + t_x, \ y' = y + t_y \quad (11)$$

i. Scale: scaling by factors s_x, s_y changes the pixel positions as:

$$x' = s_x . x, \ y' = s_y . y \quad (12)$$

j. Rotation: for rotation by θdegrees, the new coordinates are given by:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \tag{13}$$

k. Resize: resizing the image changes its resolution. For an image with original size (w_0, h_0) resizing it to a new size (w_n, h_n) can be represented as:

$$x' = x.\frac{w_n}{w_0}\ ,\ y' = y\ .\frac{h_n}{h_0} \tag{14}$$

This scales both x and y coordinates to the new target size (224×224). Several key evaluation metrics were employed, each providing valuable insights into the performance of the models.

4. RESULTS AND DISCUSSION

In this study, various models were evaluated for the task of rice leaf disease classification using training and test sets that contain 1,470 and 630 instances, respectively. The models compared include a simple CNN, Inception v3, ResNet50, EfficientNetB0, and DenseNet121. Each model was assessed based on key metrics such as accuracy, loss, precision, recall, F1 score, AUC-ROC, Matthews correlation coefficient (MCC), and hamming loss. The models were also analyzed class-wise to understand their performance on individual disease classes as in Table 1.

Table 1. Overall performance comparison

Model	Accuracy	Loss	Precision	Recall	F1 Score	AUC-ROC	MCC	Hamming loss
Simple CNN	0.924	0.678	0.924	0.924	0.923	0.9942	0.909	0.0762
EfficientNetB0	0.971	0.504	0.972	0.971	0.971	0.9987	0.966	0.0286
ResNet50	0.976	0.504	0.977	0.976	0.976	0.9994	0.972	0.0238
Inception v3	0.978	0.500	0.978	0.978	0.978	0.9992	0.973	0.0222
Proposed DenseNet121	0.984	0.278	0.984	0.984	0.984	0.9996	0.981	0.0159

Figure 4 presents a visual comparison of the training and validation accuracy across the models. Figure 4(a) through Figure 4(e) respectively depict the performance of the simple CNN, EfficientNetB0, ResNet50, Inception v3, and the proposed DenseNet121. The figure clearly illustrates the significant improvements in accuracy and convergence behavior achieved by DenseNet121 compared to other models.

Figure 5 compares the training and validation loss of the models. Figure 5(a) shows simple CNN, slow convergence and the highest validation loss. Figure 5(b) shows that EfficientNetB0 reduces loss moderately but requires more epochs to stabilize. Figure 5(c) shows that ResNet50 achieves steady training loss reduction but exhibits fluctuating validation loss, indicating overfitting. Figure 5(d) shows that InceptionV3 demonstrates robust loss reduction with stable validation loss, showcasing a balanced architecture. Finally, Figure 5(e) shows that DenseNet121 achieves the lowest final validation loss with consistent improvement, highlighting superior generalization.

Figure 6 highlights the performance metrics across models, focusing on test accuracy and test loss. Figure 6(a) compares the test accuracy, where DenseNet121 achieves the highest at 98.41%, followed by ResNet50 (97.61%), Inception v3 (97.78%), and EfficientNetB0 (97.14%). Figure 6(b) compares test loss, with DenseNet121 demonstrating the lowest at 0.2777, indicating excellent generalization, while ResNet50, Inception v3, and EfficientNetB0 show higher losses of 0.5036, 0.4996, and 0.5042, respectively.

The confusion matrix comparison highlights the performance of different models in identifying and diagnosing various rice disease classes. The comparison of CNN models highlights their classification accuracy across six classes (CL1 to CL6). Simple CNN shows moderate performance with notable misclassifications, particularly in CL2 and CL6. EfficientNetB0 improves with higher accuracies, especially for CL2 and CL6. ResNet50 demonstrates exceptional accuracy, achieving over 95% for all classes, with minimal misclassification. Inception v3 delivers comparable results to ResNet50, with slightly more misclassifications in CL4 and CL5. DenseNet121 also excels, matching ResNet50 and Inception v3 in overall accuracy, with slight misclassification in CL4 and CL5. ResNet50 and DenseNet121 emerge as the most reliable models for accurate classification across all classes. Inception v3 also achieves high accuracy, with minimal misclassifications, primarily in CL2 and CL4. The proposed DenseNet121 model demonstrates superior performance, accurately classifying all instances of CL1, CL3, and CL6 with minimal errors in the remaining classes. Overall, DenseNet121 achieves the best results, highlighting its robustness and precision in classifying rice leaf diseases compared to the other models.

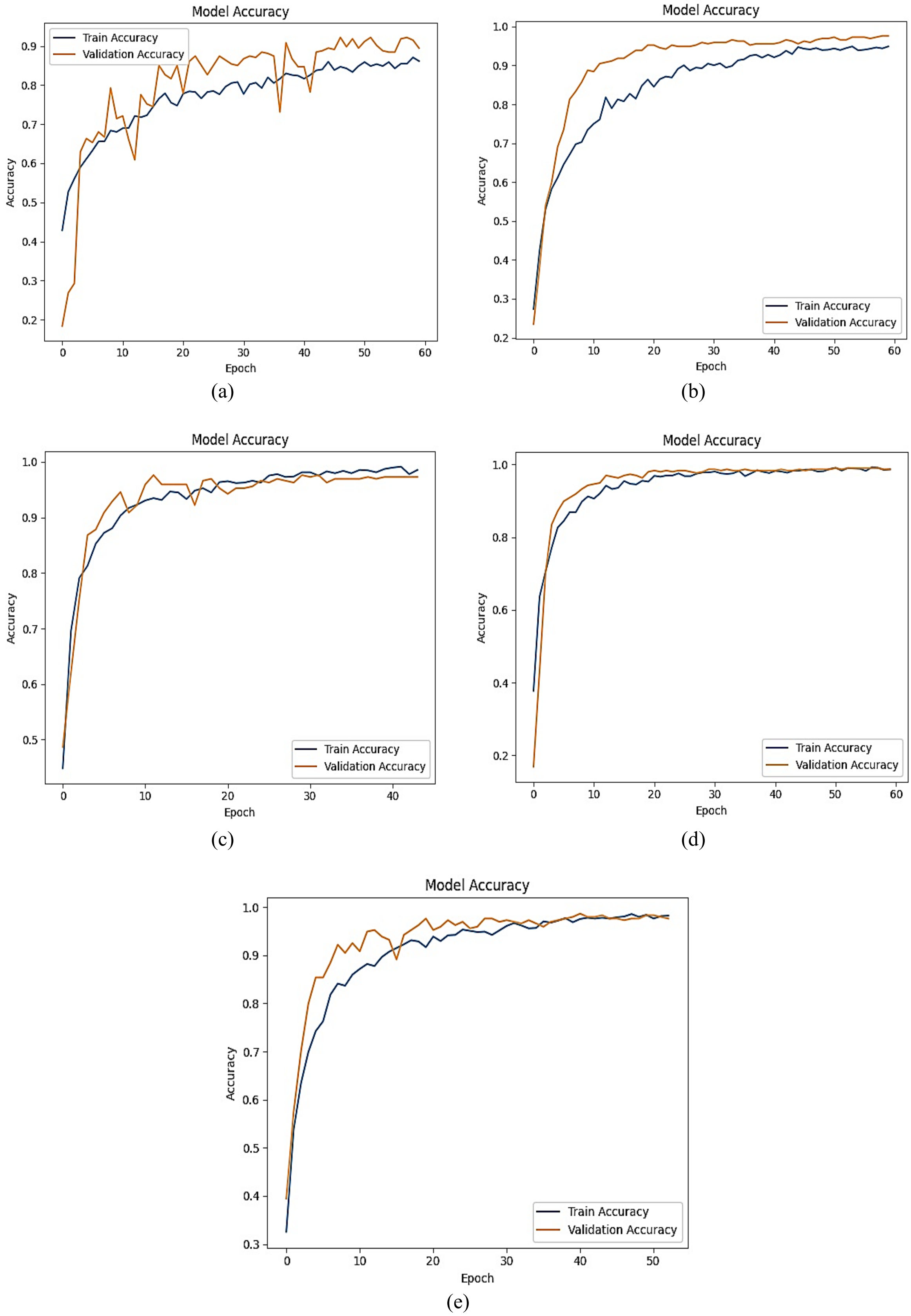
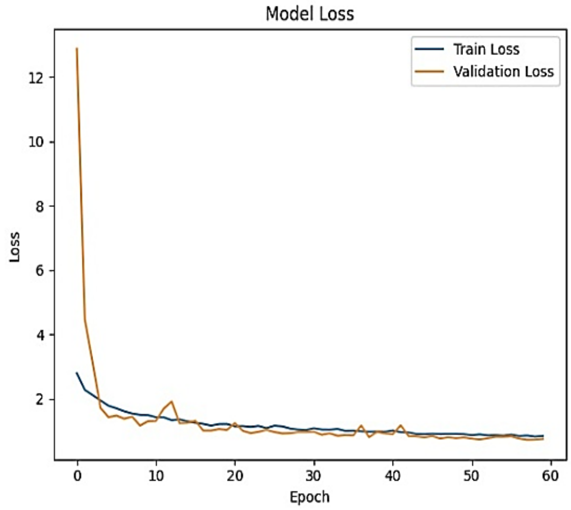
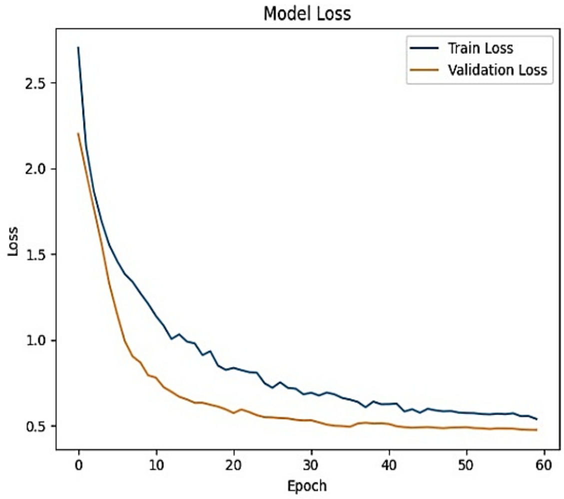


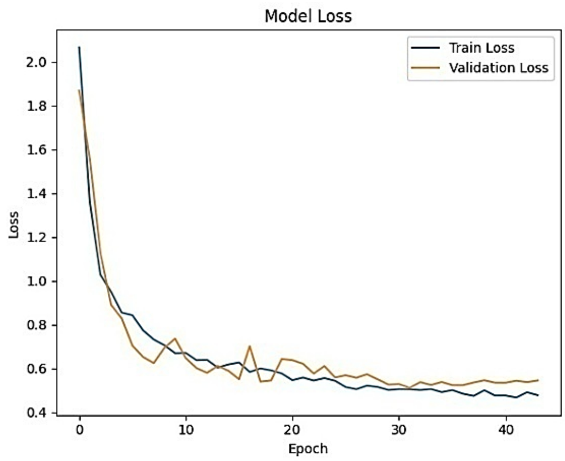
Figure 4. Comparison of training and validation accuracy of (a) simple CNN (b) EfficientNetB0, (c) RestNet50 (d) Inception v3 (e) proposed DenseNet121



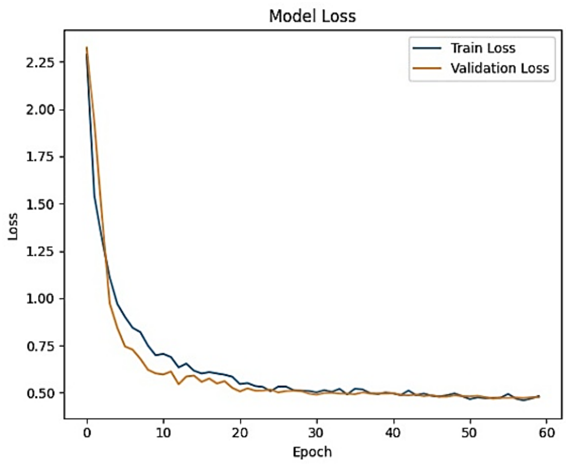
(a)



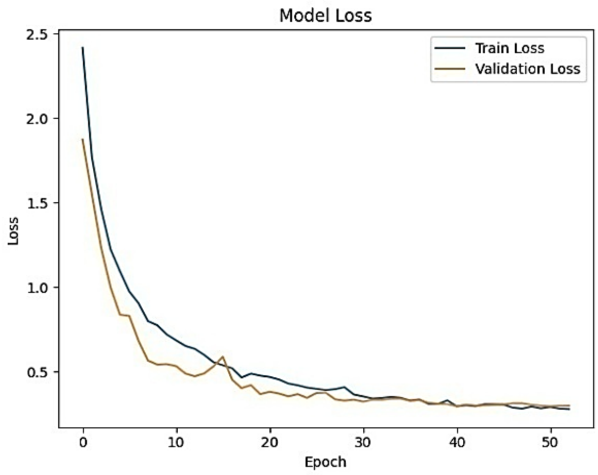
(b)



(c)

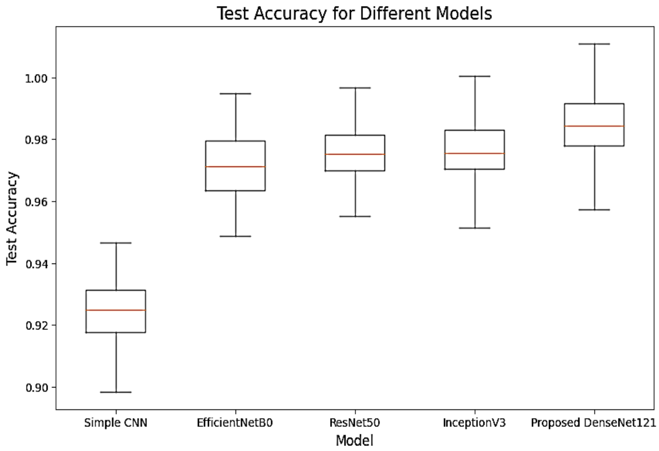


(d)

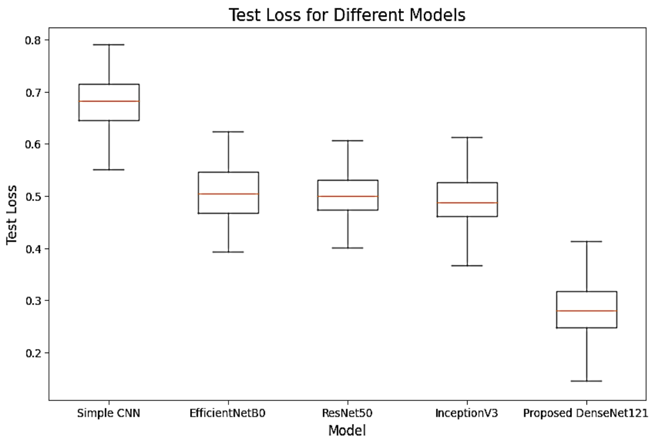


(e)

Figure 5. Comparison of training and validation loss of (a) simple CNN, (b) EfficientNetB0, (c) RestNet50 (d) Inception v3, (e) proposed DenseNet121



(a)



(b)

Figure 6. Comparison of (a) test accuracy and (b) test loss with different models

5. CONCLUSION

The proposed method demonstrates the effectiveness of using advanced deep learning architectures combined with sophisticated image augmentation techniques for rice leaf disease classification. By evaluating five models: Simple CNN, EfficientNetB0, ResNet50, Inception v3, and DenseNet121, the study confirms that DenseNet121 achieved the highest accuracy of 98.41%, with superior precision, recall, and F1 scores across six disease classes. The use of a custom data generator with advanced augmentations, including Gaussian blur, noise addition, and brightness/contrast adjustments, proved crucial in enhancing model robustness and generalization. Furthermore, the integration of L2 regularization, dropout strategies, and a custom learning rate scheduler contributed to reducing overfitting and improving convergence. The results underline the importance of advanced data preprocessing and regularization in achieving high-performance disease classification models, with DenseNet121 emerging as the most reliable architecture for this task. These findings offer significant contributions to automated agricultural disease detection, paving the way for more effective and scalable solutions in precision farming. Future work will involve exploring cutting-edge deep learning architectures, such as vision transformers (ViT) or hybrid models combining CNNs and attention mechanisms, which could lead to even higher accuracy and robustness. The integration of explainable artificial intelligence (XAI) techniques would also enhance the interpretability of these models, allowing farmers and agricultural experts to understand the reasoning behind the classification decisions.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Govindarajan S	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Mary Vennila S		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest regarding the publication of this paper.

DATA AVAILABILITY

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Govindarajan Subburaman completed B.Sc. in computer science (2009) from Bharathidasan University, Tiruchirappalli, India and M.Sc. in computer science (2012) from Bharathidasan University, Tiruchirappalli, India. He completed his M.Phil. (computer science) in the year 2014 from Bharathidasan University, Tiruchirappalli, India and currently pursing Ph.D. in computer science from Presidency College, Chennai. His area of interest include data mining, cloud computing, machine learning and deep learning. He can be contacted at thimagovind7@gmail.com.

Mary Vennila Selvadurai completed B.Sc. in physics (1986) and M.Sc. in computer science (1990) from Bharathidasan University, Tiruchirappalli, India. She obtained her M.Phil (computer science) in the year 2002 and Ph.D. in computer science (2009) from Mother Teresa Women's University, Kodaikanal. She is currently working as an associate professor and head of the PG and research department of computer science, Presidency College, Chennai, India. Her areas of interest include networks, grid computing, cloud security and data mining. She can be contacted at maryvennila13@gmail.com.