Rice leaf disease classification using depthwise separable convolutional neural network

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Abstract. Given the significant impact of rice leaf diseases on agricultural productivity, early and accurate disease identification is imperative. This study proposes the use of Depthwise Separable Convolutional Neural Networks (DSCNN) for efficient classification of rice leaf diseases. By effectively separating image pixels into different classes based on their characteristics, DSCNN provides a robust solution to this task. The proposed methodology involves preprocessing steps such as resizing, noise reduction using Laplacian, contrast enhancement using CLAHE, and data augmentation. The proposed CNN model has been evaluated with different loss functions along with varying learning rates. 20 iterations using RMSprop Optimizer with a learning rate of 0.0001 gave the best average validation and average test accuracy of 0.8659 and 0.9898 for our proposed CNN model. Based on the performance of our model, it is clear that the proposed model is capable of accurately diagnosing various rice plant diseases. Considering the small parameter size of 2.4 million, we conclude that the proposed model is a substantial improvement over traditional convolutional neural network architectures in rice plant disease detection.

1 Introduction

The production of food crops plays a significant role in determining the domestic market conditions in our country. Rice (Oryza sativa) is one of the primary commodities with a crucial role in the agricultural sector. However, farmers often face major challenges in the form of pests and plant diseases. Maintaining the health of food crops is essential to support food security and sustainability in agricultural systems. Diseases affecting food crops can hinder growth, reduce yields, and lower product quality, making them one of the leading causes of productivity loss [1-7]. During cultivation, rice plants are highly susceptible to various diseases and pests, such as bacterial blight, blast, brown spot, and tungro virus.

Manual classification of leaf diseases in rice plants is possible due to the visible changes in leaf color and appearance caused by various pathogens. Nevertheless, human perception of color can be subjective, and the process is time-consuming for large-scale identification. Leveraging modern technology, image processing techniques combined with artificial intelligence can automate the diagnosis of rice plant diseases, offering a more objective and efficient solution [7,8].

In recent years, there has been a surge in research on rice classification using various digital image processing and artificial intelligence techniques [9-16]. Some approaches involve the use of deep neural networks and optimization algorithms to improve disease identification accuracy. For instance, Ramesh and Vydeki employed a neural network model optimized with the Jaya algorithm to identify four types of rice diseases and performed binary image extraction from hue and saturation differences after converting RGB images to HSV [17]. Another study by N. Krishnamoorthy et al. [18] utilized the InceptionResNetV2 model to detect several rice leaf diseases. By employing transfer learning and hyperparameter tuning, the model achieved an accuracy of 95.67%. Furthermore, Shrivastava et al. [19] applied the AlexNet model with transfer learning to detect 3 types of rice plant diseases, resulting in a classification accuracy of 91.73%. Other research also achieved automatic rice leaf using image processing. [20,21,22]

While these approaches have shown promising results, this research proposes a more efficient and computationally lightweight method using Depthwise Separable Convolutional Neural Network (DSCNN) for rice leaf disease classification. DSCNN is a type of CNN architecture that can significantly reduce the number of parameters and computational operations without sacrificing accuracy performance. By separating the convolution process into two stages, namely depthwise convolution and pointwise convolution, DSCNN is expected to accelerate the inference process and minimize computational resource requirements.

The novelty of this research lies in the proposed use of DSCNN for rice leaf disease identification, which has not been widely implemented in previous studies. This approach is expected to enhance efficiency in rice leaf disease classification with competitive accuracy compared to previous models, while also enabling broader applications in various field conditions.

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2 Method

This section explains the research stages that must be carried out to obtain rice leaf disease classification results. Figure 1 shows the research flow.

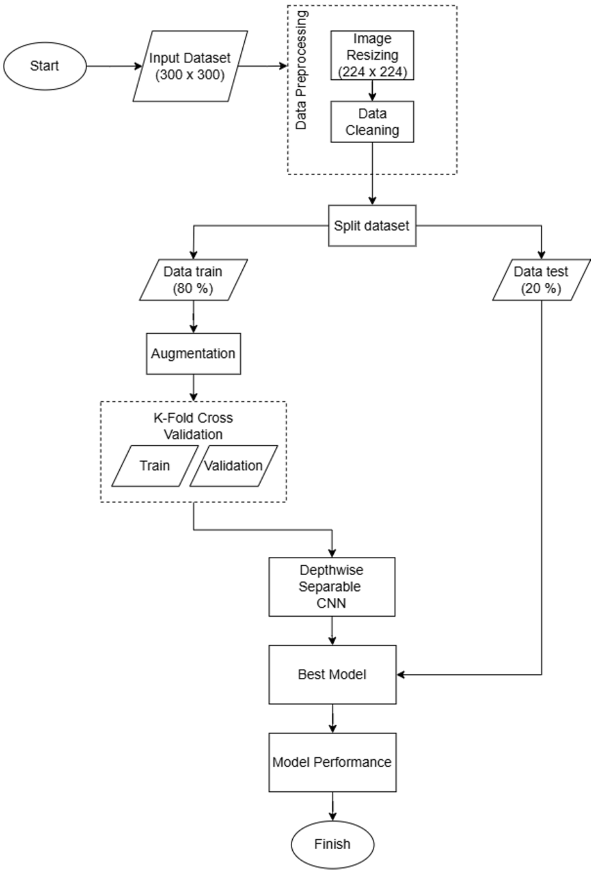

Fig. 1. Research flow.

2.1 Dataset collection

The dataset used in this research is a collection of rice leaf disease images entitled "Rice Leaf Disease Image Samples". This dataset was taken from research entitled "Deep Feature-Based Rice Leaf Disease Identification Using Support Vector Machine" [23]. The dataset consists of 5932 images of rice leaf diseases which are divided into four classes, namely bacterial blight, brown spot, blast, and tungro. Examples of images for each class of rice leaf disease can be seen in the following Figure 2.

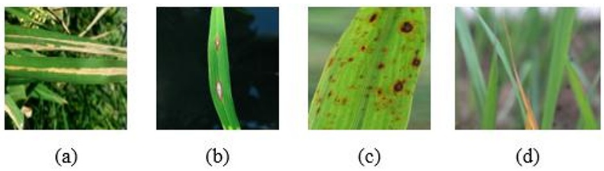

Fig. 2. Rice leaf disease (a) bacterial blight, (b) blast, (c) brown spot, (d) tungro.

From the total data of 5932 rice leaf disease images, each class has the amount of data that can be seen in Table 1.

Table 1. Number of data in each class.

Class	Number of images
Bacterial blight	1584
Blast	1440
Brown spot	1600
Tungro	1308

2.2 Data preprocessing

Data preprocessing is a crucial step to ensure the quality and consistency of the input data prior to feeding it into the model. In this study, preprocessing involves resizing images to a standardized dimension, noise reduction, and contrast enhancement. Subsequently, data augmentation techniques are employed to expand the dataset, thereby enabling the model to generalize more effectively.

2.2.1 Image resizing

Image resizing is performed to meet architectural requirements, where the original dimensions of 300 x 300 pixels are reduced to 224 x 224 pixels. This reduction in size helps lower computational costs, allowing the model to focus on more relevant features.

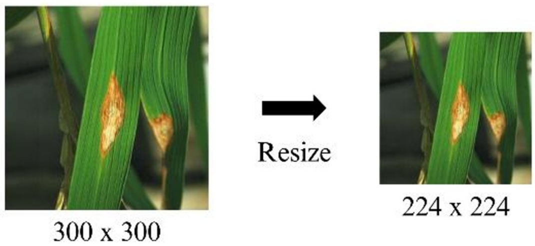

Fig. 3. Image resizing.

Figure 3 illustrates the image resizing process, where the original 300 x 300 pixel image is reduced to the required 224 x 224 pixel size. This step ensures consistency in image dimensions throughout the dataset while optimizing the images for feature extraction within the model's architecture. By standardizing input dimensions, resizing improves the model's learning efficiency and accuracy, aiding in its ability to effectively identify and classify various rice leaf diseases.

2.2.2 Noise reduction and contrast enhancement

Removing noise or blur in image data can be done using the Laplacian method to detect blurry images. Laplacian is a second-order derivative-based edge detection operator that works by calculating changes in pixel intensity. Blurred images can be detected because they usually have little detail and less sharp edges. After that, the CLAHE (Contrast Limited Adaptive Histogram Equalization) method is applied to increase the contrast in the image. Images with low contrast often trigger errors in the form of false positive and false negative ratios, which ultimately result in low accuracy in the analysis process.

The CLAHE method, as described by Pizer et al. [24], is an adaptive contrast enhancement technique that works by adjusting the histogram in small sections (tiles) of the image. In contrast to conventional histogram equalization, CLAHE limits the degree of histogram amplification by truncating the histogram at a certain value before calculating the cumulative distribution function (CDF). This clipping value depends on the normalization of the histogram and the size of the local area being processed.

The combined use of the Laplacian method for blur detection and CLAHE for contrast enhancement proved effective in improving image quality. This can be seen from the comparison between images (a) and (b), as well as the changes in RGB color distribution shown in graphs (c) and (d). This process is very useful in increasing the accuracy of image analysis, both for leaf identification and other applications that require high quality images.

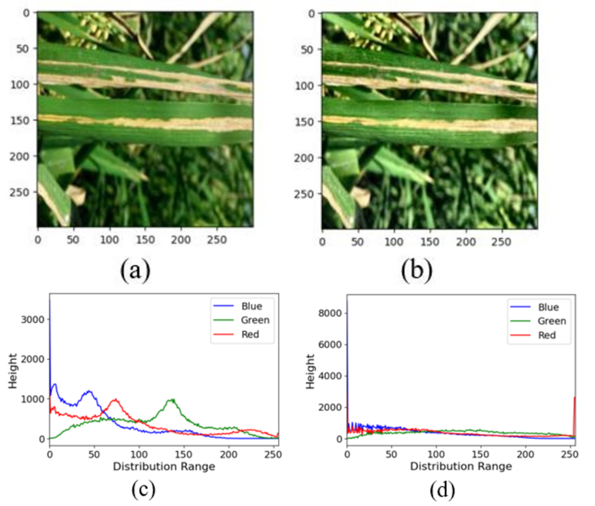

Fig. 4. Contrast limited adaptive histogram equalization method (a) low contrast input image, (b) high contrast output image, (c) RGB channel of input image, (d) RGB channel of output image.

2.2.3 Data augmentation

Data augmentation was performed to increase the dataset size by applying several techniques from ImageDataGenerator. The techniques employed include rotation with a rotation_range parameter of 40, which randomly rotates the image within a range of 0 to 40 degrees. Subsequently, shifting was applied to both the width and height with a range parameter of 20% for horizontal and vertical shifts from the original image size. The third technique, shearing, randomly shears the image within a range of 20%. The fourth technique is zooming, which randomly zooms the image up to 20%. Next, flipping is applied to randomly flip the image horizontally. Finally, fill mode is used to fill pixel values in empty areas with the nearest pixel values. This process increased the total number of images from the initial 5.932 to 12.308.

Table 2 shows the distribution of the number of images in the dataset for rice plant disease classification after augmentation and data splitting. The data is split with a ratio of 80% for training and 20% for testing. After splitting, the training data is divided again into train and validation using K-fold cross validation with a value of K = 10 which will divide the data into 10 equal parts. This division is applied to ensure that the dataset is representative enough to accurately train, validate, and test model performance.

Table 2. Dataset distribution.

Class	Number of images	Training set	Validation set	Testing set
Bacterial blight	4610	3951	439	220
Blast	2568	2200	245	123
Brown spot	3350	2871	319	160
Tungro	1780	1525	170	85

2.3 Experimental setup

To validate our research hypothesis, we carried out experiments to assess the performance of the DSCNN model in classifying rice leaf disease images. The experimental setups are summarized in the Table 3.

Table 3. Experimental setup.

Optimizer	Learning rate
Adam	0.01
	0.001
	0.0001
RMSprop	0.01
	0.001
	0.0001
Hinge loss	0.01
	0.001
	0.0001
SGD	0.01
	0.001
	0.0001

This study was conducted by comparing the performance of models using various combinations of optimizer algorithms and learning rate values. Optimizer is a function that aims to improve the efficiency and accuracy of model training by optimizing weight adjustments in the learning system. Each optimizer algorithm works with a certain learning rate value that determines how fast or slow the model learns from the data. Some commonly used optimizer algorithms are Root Mean Square Propagation (RMSprop), Adaptive Moment Estimation (Adam), and Stochastic Gradient Descent (SGD). In this study, the three algorithms were used to test the performance of the model in various scenarios.

Meanwhile, the learning rate is an important parameter that controls the magnitude of the weight change during the training process. This parameter acts as a multiplier on the gradient value calculated by the gradient descent algorithm, which determines the step size in the gradient direction. The gradient serves to guide the model towards a flatter minima, which is often associated with better generalization ability [25]. The gradient vector on each data has a certain magnitude and direction, so choosing the right learning rate value is very important. If the learning rate value is too large, the model can become unstable and fail to reach convergence. On the other hand, if it is too small, the training process will be slow and take a long time to achieve optimal results. Therefore, this study evaluates the effect of various combinations of optimizer algorithms and learning rate values to determine the best configuration that produces optimal model performance.

3 Result and discussion

3.1 Comparison with state-of-the-art CNN models

For the training process on a powerful CNN architecture using transfer learning, each model has pre-trained ImageNet weights associated with it. The 10-fold cross-validation accuracy has been considered as the model performance metric. using different training, validation, and testing sets for several examples and recording the average results. Table 4 shows the average training, validation, and testing results after 20 iterations on the rice disease dataset on various state-of-the-art CNN architectures. It is seen that transfer learning models such as DenseNet-121 excel in training, validation, and testing accuracies due to the pre-learned features. DSCNN, despite being trained from scratch, provides a competitive test accuracy (0.9898) with a relatively small number of parameters, indicating its potential for applications requiring lightweight models.

The DSCNN architecture model generates a total of 2.4 million parameters, including trainable and non-trainable parameters. These parameters consist of weights and biases at each layer of the model. Trainable parameters are values that are updated during the training process through optimization algorithms such as backpropagation. Typically, these parameters include weights from convolutional layers, dense layers, and other layers designed to learn patterns from training data. Most of the parameters in the model fall into this category because of their important function in learning data.

Meanwhile, non-trainable parameters are values that are fixed and not optimized during training. These parameters generally come from layers such as Batch Normalization, which have attributes such as moving mean and moving variance. These attributes are used to stabilize the data distribution during inference and do not change during the training process.

Compared with other state-of-the-art CNN models, DSCNN has the advantage of a smaller number of parameters, making it more efficient in terms of memory usage and computing power. This makes DSCNN an ideal choice for applications that require high efficiency, such as low-power devices or real-time systems.

The proportion of trainable and non-trainable parameters reflects the balance between the model's ability to learn and its stability. Trainable parameters determine the model's capacity to learn patterns from data, while non-trainable parameters serve to maintain stability and ensure efficiency, especially in managing data distribution during inference. This balance plays an important role in influencing model performance, both at the training and inference stages.

The performance curve of 4 state of the art CNN architectures are shown in Figure 5 with transfer learning validation accuracy. MobileNet V2, DenseNet-121, and Xception almost immediately achieve very high validation accuracy in early iterations and remain stable throughout training. This highlights the efficiency of transfer learning methods for these models. VGG 16 requires more iterations to achieve performance close to that of other models. The slower performance can be attributed to the older architecture and its complexity. For tasks that require fast results, architectures such as MobileNet V2 and DenseNet-121 are more recommended as they reach optimal performance faster.

Table 4. Statistical analysis of various CNN architectures on rice plant disease dataset.

Model	Mean Train Accuracy	Mean Validation Accuracy	Mean Test Accuracy	Total Parameter
Mobile Net V2	0.9937	0.9911	0.9945	3.573.828
Xception	0.9929	0.9854	0.9902	22.963.756
DenseNet-121	0.9934	0.9933	0.9984	8.091.204
VGG 16	0.9477	0.9454	0.9844	15.244.100
DSCNN	0.9426	0.8659	0.9898	2.456.036

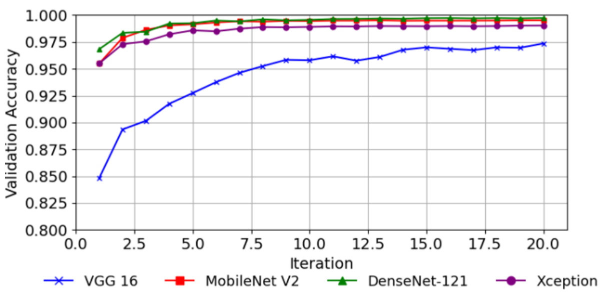

Fig. 5. Performance curve of different CNN models on transfer learning.

3.2 Proposed CNN model performance

In the training process of a Depthwise Separable Convolutional Neural Network (DSCNN) model, two training scenarios were conducted using different optimizers: Adam, RMSprop (Root Mean Square propagation), HingeLoss, and SGD (Stochastic Gradient Descent). Each optimizer was tested with three different learning rates: 0.01, 0.001, and 0.0001, to determine the best configuration that yields the highest accuracy in rice leaf disease classification.

Each combination of optimizer and learning rate will be evaluated using accuracy and loss metrics on the training and validation data to observe the model's performance. The results of these various configurations will be compared to determine the best combination that provides optimal classification results on the rice leaf disease dataset. The results are shown in Table 5.

Table 5. Result test scenario.

Optimizer	Learning rate	Mean validation accuracy
	0.01	0.5620
Adam	0.001	0.7510
	0.0001	0.8590
	0.01	0.3655
RMSprop	0.001	0.8228
	0.0001	0.8659
	0.01	0.3416
Hinge loss	0.001	0.5385
	0.0001	0.8085
	0.01	0.7646
SGD	0.001	0.7941
	0.0001	0.7889

Based on the table above, it is known that the DSCNN model which has the best performance in classifying rice leaf disease images is the one with RMSprop as its optimizer and a learning rate of 0.0001, resulting in a mean validation accuracy of 0.8659.

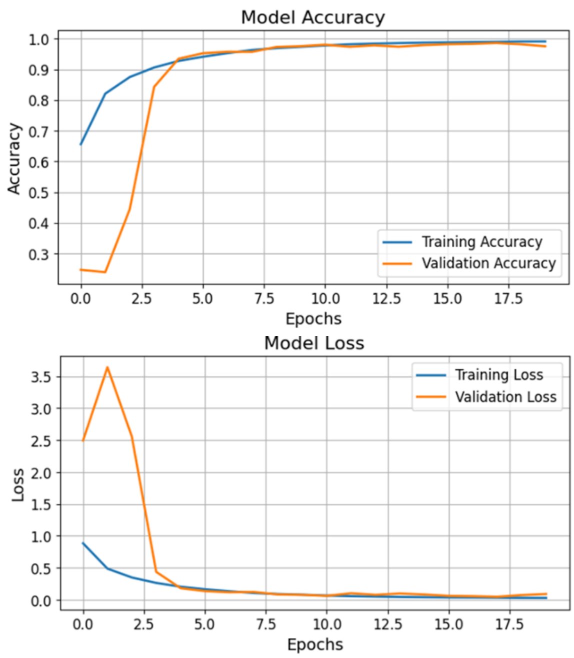

Fig. 6. Performance curve of the proposed CNN model using RMSprop optimizer with 0.001 learning rate.

Figure 6 shows the accuracy and loss graphs for training and validation on the DSCNN model when the RMSprop optimizer with a learning rate of 0.0001 is used, and the training process is conducted for 20 iterations. The DSCNN model demonstrates a good performance as both graphs (accuracy and loss) show a stable improvement. The high accuracy on validation data and the consistent decrease in loss indicate that the model is well-trained without significant signs of overfitting.

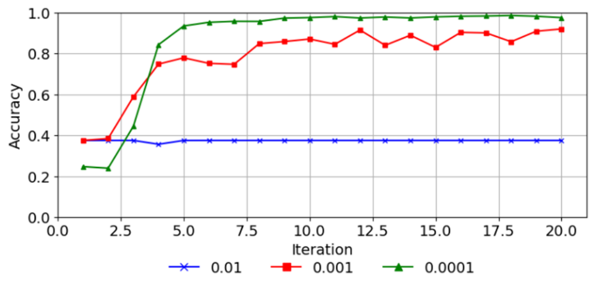

Fig. 7. RMSprop optimizer with variable learning rate.

Figure 7 shows the validation accuracy over 20 iterations for three different learning rates: 0.01 (blue), 0.001 (red), and 0.0001 (green). The learning rate of 0.01 exhibits a slow increase in validation accuracy at the beginning of the iterations (up to the 5th iteration) but remains relatively low overall, around 0.4-0.5. This indicates that a learning rate of 0.01 might be too large for this model, making it difficult for the model to converge well. The learning rate of 0.001 shows a steady increase in validation accuracy until it peaks around the 5th iteration, with an accuracy of around 0.8. After that, the accuracy tends to stabilize but fluctuates slightly in the range of 0.75-0.85. This learning rate seems to be quite optimal, providing a balance between convergence speed and stability. The learning rate of 0.0001 shows a rapid increase in validation accuracy at the beginning of the iterations (faster than the learning rate of 0.001), reaching a value of around 0.9 at the 5th iteration. After the 5th iteration, the curve shows high stability with accuracy in the range of 0.9-0.95. This learning rate results in the most stable and accurate model compared to the other two learning rates.

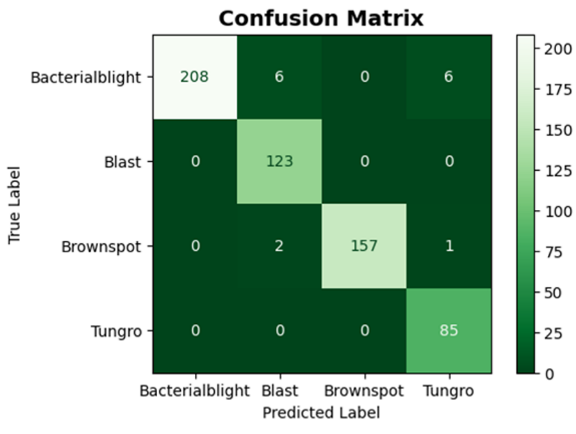

Fig. 8. Confusion matrix.

Figure 8 shows the confusion matrix for the DSCNN model using the RMSprop optimizer with a learning rate of 0.0001, which is the DSCNN model with the best performance during training. This confusion matrix represents four classes: bacterial blight, blast, brownspot, and tungro, which are represented by rows and columns. For the bacterial blight class, the model was successful in correctly predicting 208 image examples, with 6 misclassifications to the blast class and 6 to tungro. The blast class had 123 images classified correctly, with no misclassifications to other classes. The brownspot class had 157 images correctly classified, with 2 misclassifications to the bacterial blight class and 1 to tungro. Finally, the tungro class had 85 images classified correctly, with no misclassifications to other classes.

Table 6 presents a comparison between the current study and previous research using the same dataset of 5932 images from four classes, curated by Prabira Kumar Sethy. In earlier work by Prabira Kumar Sethy et al., a feature-based rice leaf disease identification method was employed, utilizing the SVM algorithm along with deep feature extractors like ResNet-50 and MobileNet V2. Their results demonstrated high accuracy, achieving 98.38% with ResNet-50 + SVM and 97.96% with MobileNet V2 + SVM.

In contrast, the present study employed a DSCNN model on the same dataset. After 20 iterations, this model achieved an accuracy of 87.51%, which is slightly lower than the previous methods. This comparison indicates that approaches based on deep feature extractors, such as ResNet-50 + SVM, tend to yield better performance in classification tasks with this dataset.

Table 6. Comparison of current research with other journals on the same dataset.

Authors	Proposed Method	Dataset	Iteration	Performance
Prabira Kumar Sethy et al [8]	Rice leaf disease identification by SVM based on deep feature	collection of 5932 images of 4 classes curated by contributor Prabira Kumar Sethy	-	ResNet 50 + SVM = 98,38 % MobileNet V2 + SVM = 97,96%
Current Research	Depthwise Separable Convolution Neural Network	collection of 5932 images of 4 classes curated by contributor Prabira Kumar Sethy	20	DSCNN = 87,51%

3.3 Discussion

This study explores the application of Depthwise Separable Convolutional Neural Network (DSCNN) to classify rice leaf diseases, leveraging its computational efficiency and competitive accuracy. The study covers the workflow from dataset preprocessing, data augmentation, to DSCNN model implementation with optimal hyperparameter tuning. The results show that the DSCNN model achieves fairly good testing and validation accuracies, highlighting its capability in identifying rice leaf diseases. Compared to other state-of-the-art CNN architectures, such as DenseNet-121 and MobileNet V2, DSCNN shows competitive performance despite having much fewer parameters, around 2.4 million. Its lightweight nature makes it ideal for deployment in resource-constrained environments, such as on mobile devices or edge devices.

Although the performance of the DSCNN model is slightly lower compared to models using transfer learning, this result is achieved without such assistance, reflecting the robustness of the model when trained from scratch. The efficient design of DSCNN, with depthwise and pointwise convolutions, provides advantages in terms of computational cost while maintaining accuracy. Training the DSCNN model with various hyperparameter configurations shows that the choice of learning rate is very important for training stability and achieving optimal accuracy. Small learning rates, such as 0.0001, tend to give better results in almost all optimizers, especially RmsProp which shows the highest accuracy. Adam and RmsProp optimizers also show better performance compared to HingeLoss and SGD in terms of validation accuracy. Choosing the right learning rate is the key to success, because too high a learning rate can cause unstable training, while too low a learning rate can slow down the convergence process.

4 Conclusion

In this study, a depthwise separable convolutional neural network model has been proposed that is able to effectively identify 4 types of rice plant diseases. The dataset used consists of images obtained from public sources. During the pre-processing stage, the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm is applied to improve the contrast quality of the images. In addition, various image augmentation techniques are used to expand the dataset, increasing the number of samples to 12.308 images.

For comparison, 4 state-of-the-art CNN architectures are also applied to this dataset. Among all the tested architectures, DenseNet-121 shows the best performance with a validation accuracy of 0.9933 and a testing accuracy of 0.9984. The proposed CNN model is evaluated using several loss functions and different learning rates. The use of the RMSprop optimizer with a learning rate of 0.0001 produces the best average validation accuracy of 0.8659 and an average testing accuracy of 0.9898 for the proposed model.

These results show that the proposed model is able to accurately diagnose various diseases in rice plants. With a relatively small number of parameters, namely 2.4 million, this model is proven to be more efficient than conventional CNN architectures in detecting rice plant diseases. This makes it a significant and effective solution for rice disease diagnosis applications.

This research is one of the outputs of Penelitian Mandiri, LPPM, University of Trunodjoyo Madura.

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