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A Deep Learning-Based Technique for Classification of Rice Leaf Disease Using Transfer Learning

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Abstract

Rice is a staple food and a gluten-free grain. According to a survey on agriculture and natural resources with international plant pathology by the University of California, rice leaf diseases highly affect rice production loss. Scientists, farmers, and the management team are always on the hunt for a method for early detection and classification of rice leaf diseases. Such a method will facilitate accurate and prompt treatment of diseases and will prevent their spread. Deep learning techniques provide an edge over the manual way of classification in many ways. Our work uses a deep learning-based approach for rice leaf disease classification. MobileNetV2 is used along with transfer learning for classification. The main purpose of this research is to utilize a challenging dataset that is not carefully selected and exploit transfer learning techniques. The functional capabilities of the classification model are improved by a reduction in the training time and parameter size optimization. Four different datasets that contained different characteristics were collected. These datasets were then combined to construct a combined dataset of 7,445 images containing five types of rice leaf diseases. The proposed model and another convolutional neural network (CNN) have been used as baseline models on the five datasets and results have been analyzed. According to the experimental analysis, the proposed model has the best classification accuracy of 99.17%. It provides a significant increase in accuracy using fewer parameters as compared to other models. Experimental findings show the feasibility and efficiency of the proposed model.

Keywords: *Augmentation; depth-wise separable convolutions; intra-class similarity; hyper-parameters; pre-processing*

1. Introduction

Food crops are livelihood crops that are meant for human utilization. For example, fruits, vegetables, and grains. Grains include wheat, rice, corn etc. Rice is a Cereal Grain. It is a source of energy for more than half of the World's population. According to the UN's hunger report hunger is the period in which human faces severe food insecurity (W.H.K.F.A., 2022). Food insecurity is the deficiency of consistent gain of food for every person to live an active and healthy life (FAO, 2020). It is the state in which uncertain access of adequate food occurs.

A report of action against hunger stated that 811 million people are facing hunger (W.H.K.F.A.,

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2022). Hunger affecting rate is 9.9 percent of people Worldwide. Pakistan's Ministry of Health and UNESCO in the National Nutritional Survey noted that Pakistan is among those seven countries worldwide that are afflicted with malnutrition and ill-fed population (Iqbal, 2019). Major causes of the undernourished population are high growth levels of population and unfavorable conditions for crops. It results in a low gain of food in our own country. Half of the children of age under five years face low height for age challenge and one out of ten faces low weight for height challenge.

Rice is a staple food and gluten-free grain. Two major categories of rice are Asian rice and African rice. It is considered to be an energy source in 34 countries. With population growth demand for this necessary food is increasing. Statista surveyed on the consumption of rice from the year 2008 to January 2022 (Shahbandeh,2022). The rate of rice consumption is increasing. In 2008-2009 rice consumption rate was 437.18 million metric tons. Now this rate reaches up to 509.87 million metric tons. The increased ration of rice consumption is much higher than past year's ratio.

The rice sector demands industry stated rice production estimation for the year 2022/2023 is 8 million tons (Hanif, 2022). This production depends on many factors (Salgotra, B.B.G., and Raina 2017). These include biotic stresses/diseases brought on by bacteria, fungi, and viruses, abiotic stresses/psychological disorders, greenhouse gas emissions, resource scarcity, improper farming methods, and the growing population. All of these result in a decrease in rice yield (Tsuboi, 2012). Therefore, these elements must be under control for successful cultivation. Focused research for aiding the efficient cultivation of crops is the need for time to provide a risk-free food supply.

In this research, weights of pre-trained MobileNetV2 are used for the classification of rice leaf diseases. These weights perform feature extraction from the rice leaf diseases dataset. Various hyperparameters are used for fine-tuning the classifier. The main contribution of this paper is to collect datasets for the experimental process and analysis of deep learning models and fine-tune the hyperparameters. Five deep learning models with five different datasets are used and the results obtained are analyzed.

2. Related Works

Traditionally direct methods, indirect methods, and portable sensor-based plant disease detection methods have been used for the detection and classification of diseases in rice leaves. Direct methods are polymerase chain reaction, fluorescence in-situ hybridization, enzyme-linked immunosorbent assay, immunofluorescence, flow cytometry, and colony-forming unit. Indirect methods include thermography, fluorescence imaging, and hyperspectral techniques. Portable sensors make use of biosensor platforms based on nanomaterials, affinity biosensors, enzymatic biochemical sensors, and/or bacteriophage biosensors for disease detection and classification (Fang & Ramasamy, 2015).

In the current era, Artificial Intelligence (AI), digital image processing, machine learning, and deep learning techniques (Xu, 2017) came forward to perform complex tasks. They produced excellent results as compared to other techniques that were time and resource-consuming. In disease classification AI based classifiers performed remarkable detection and classification of diseases. This led to a prompt and expedient solution to the problem, thus saving the plants from diseases. Convolutional neural network gives promising results among the classifiers used to perform this task. Upaddhyay & Kumar proposed a fully connected CNN to classify rice leaf diseases from images (Upadhyay & Kumar, 2021). The original dataset contained only three classes, so Patarapuwadol *et al.* created a bigger dataset named K5RD using data augmentation techniques and experimented with learning rate adjustment strategies (Patarapuwadol et al., 2021). A multi-stage CNN configuration comprising of convolution layer, stochastic pooling layer, and SoftMax layer was used for identifying rice diseases (Lu et al. 2017). The proposed architecture was hierarchical in nature. Edges, lines, and other low-level features from the input images were extracted using the first convolutional layer. The other two were capable of extracting advanced features.

Transfer learning is a method by which a pre-trained CNN can be re-purposed for a dataset other than the one it is trained on. Transfer learning transfers the knowledge that is the weights. These weights perform feature extraction from a dataset (Costa, 2017). Details about transfer learning can be found in (Rosebrock, 2019). Different researchers used transfer learning with SVM classifier (Hasan et al., 2019), VGG16 (Anami et al. 2020, VGG19 architecture (Anami, Malvade &Palaiah, 2020), and Alex Net (Matin et al., 2020) for rice leaf disease classification. Alex Net was used to develop an early warning tool, it was further enhanced to build an integrated plant disease identification system that was fully capable of functioning in actual cultivation conditions (Bharathi, 2020). Ensemble methods containing DenseNet-121, SE-ResNet-50, and ResNeSt-50 as sub-models were also proposed for disease classification (Deng et al., 2021). An experimental analysis by large-scale state of art methods as baseline methods was performed and a two-stage CNN was created (Rahman et al.,2020). It performed a comparison with other models such as Mobile Net, Nas Net, and Squeeze Net, and gave promising results. SE-MobileNet based on MobileNet with squeeze and excitation mechanisms was proposed by Chen et al. Traditional Mobile Net's network topology was reformed to improve its capability for learning the tiny disease spots. Transfer learning was performed twice to reduce the training time of the model (Chen et al., 2021). MobileNet-V2 incorporated the attention mechanism to learn the significance of inter-channel relationships and spatial positions for input features, enhancing the learning potential for minute lesion features. Transfer learning was carried out twice for model training, and the loss function was optimized (Chen et al., 2021). Research of transfer learning with various CNN models is still in progress.

3. Materials and Methods

The proposed methodology is segregated into six steps for rice leaf disease classification. Phases of the suggested methodology are outlined in Fig. 1.

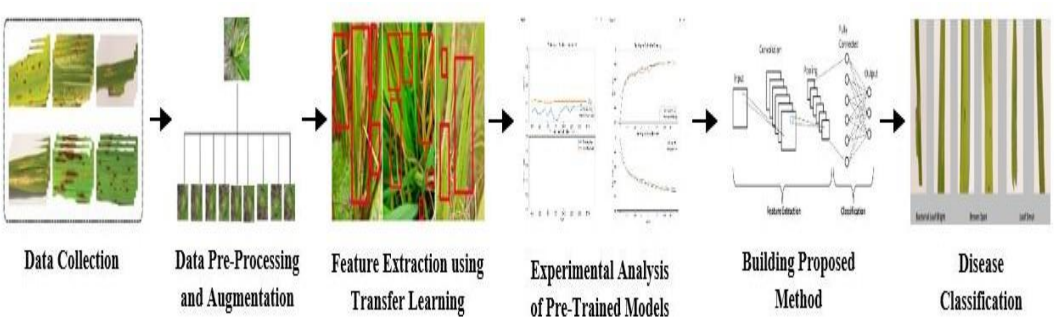

Figure 1: Block Diagram for Classification of Rice Leaf Diseases Using Transfer Learning.

3.1 Data Collection

The datasets used for the research contain different characteristics, such as; the size of the dataset, number of classes, and intra-class similarity. Some of the datasets contain noisy images while others have carefully selected images. A description of all datasets is given in Table 1.

3.1.1 Dataset A

The original name of dataset A is the rice leaf diseases dataset (Rice Leaf Diseases Dataset) [24]. It contains 120 images of three rice leaf diseases namely; bacterial leaf blight, brown spot, and leaf smut. This dataset is publicly available.

3.1.2 Dataset B

Our self-collected dataset B contains three classes of rice leaf diseases gathered from different online resources. The first class is bacterial leaf blight and it contains 1637 images. The Second is the leaf blast disease class which contains 1300 images and the third class is brown spot comprising 1600 images. All images are in .jpg format and are noise free. Images are carefully selected to check the results of the classifier.

3.1.3 Dataset C

The original name of dataset C is the rice diseases image dataset [24]. It contains 2092 images of four rice leaf diseases; brown spot, healthy, hispa, and leaf blast. This dataset is publicly available.

3.1.4 Dataset D

Dataset D contains self-collected images of four classes of rice leaf diseases in .jpg format from online resources. The first class is bacterial leaf blight and it contains 1584 images. The second class is leaf blast and it contains 1440 images. The third class is brown spot which contains 1600 images and the last class is tungro which contains 1308 images. The data is carefully selected; it does not contain noisy images. This dataset contains an increased number of rice leaf diseases in comparison to dataset B.

3.1.5 Dataset E

Dataset E is a self-collected of not carefully selected images from online resources. It contains the largest number of images and rice leaf diseases when compared to the rest of the datasets under discussion. It contains five classes of rice leaf diseases. The first class is bacterial leaf blight and it contains 1677 images. The second class is Leaf Blast which contains 2020 images. The third class is brown spot of 1640 images. Forth class is hispa which contains 800 images and the fifth class is tungro comprising 1308 images. All images are in .jpg format. What makes this dataset stand apart from the rest of the datasets is that the data is not carefully selected. This helps to assess the performance of the proposed model for images captured without a controlled environment. Another advantage is that overfitting of the model does not occur.

Table 1: Description of Datasets.

++++	Self-created Name	Dataset Original Name	Number of images	Number of Classes	Format
1	Dataset A	Rice Leaf Diseases Dataset	120	3	.jpg
2	Dataset B	Self-Collected	4,537	3	.jpg
3	Dataset C	Rice Diseases Image Dataset	2,092	4	.jpg
4	Dataset D	Self-Collected	5,932	4	.jpg
5	Dataset E	Self-Collected	7,445	5	.jpg

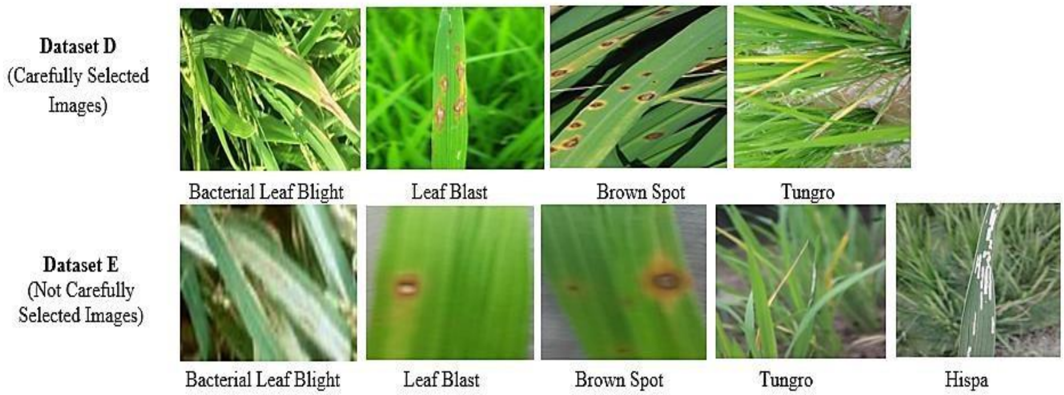

Figure 2: Various Sample Images from Self-Collected Datasets (Dataset D, Dataset E).

3.2 Data Pre-Processing and Augmentation

Data preprocessing helps prepare the raw input data and makes it suitable for developing and training a deep learning model with improved accuracy and effectiveness (Baheti, 2022). In the collected datasets images contained varied height and width and the range of images was [0-255] so we rescaled the images. Image rescaling is the process of rescaling the datasets into the value range [-1,1]. This operation was employed by tensor flow keras. When the amount of training data is small, data augmentation techniques are used for sample diversity (Takimoglu, 2021). Rotating, shearing, zooming, and flipping the images vertically and horizontally, are some of the image augmentation techniques widely used (Gong, 2021). The prime purpose of sample diversity enhancement using augmentation is to help reduce overfitting. We applied random transformations which were realistic. Rotation and flipping were applied to images in the horizontal and vertical directions. This augmentation process was employed by the Image data generator class provided by the Keras deep learning library. Rotation operation was applied on images as given in eq. (1) and (2).

gnew=gcos30-hsin30. (1)
hnew=gcos30+hsin30. (2)

Flipping operation applied to images as in eq. (3).
Current revised coordinates (a_{new}, b_{new}) = (width-a-1, b). (3)

A sample of the resultant augmented images is shown in Fig. 3.

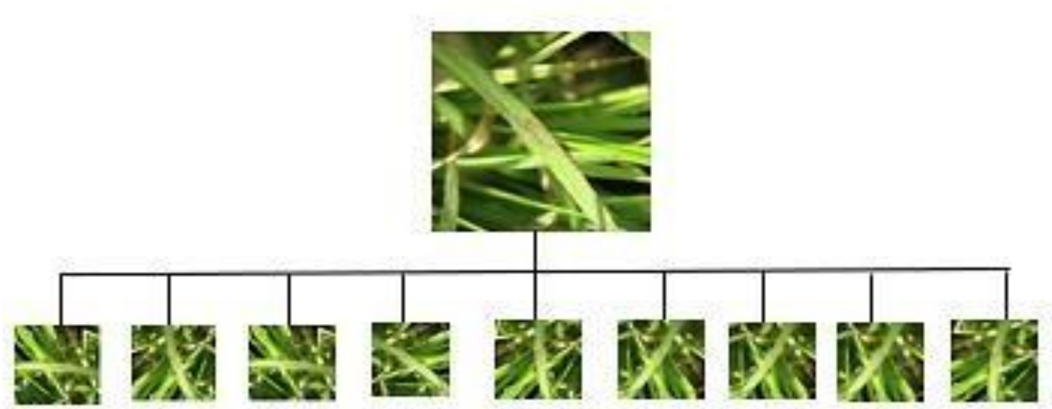

Figure 3: Augmented Image Samples Obtained Using Standard Geometric Transformations.

3.3 Experimental Analysis of Pre-Trained Models

3.3.1 Convolutional Neural Network

It is a feed-forward deep neural network. CNN captures spatial and temporal information of data and gives the best accuracy in image classification. It compares the images piece by piece. The piece that it looks for is called a feature. CNN yields commendably better results when looking for similarity in images as compared to other image-matching schemes. It contains two parts; a convolutional tool and a fully connected layer. The convolutional tool performs the identification of various image features for the feature extraction process. It consists of a convolutional layer and a pooling layer. The convolutional layer is a building block in a CNN as it confirms the spatial relationships between pixels. A kernel or filter inside this layer moves over the image's receptive fields during the convolution process to determine whether a feature is present or not. It comes before the output layer. Input comes from previous layers, gets flattened, and passes through various mathematical operations (Gurucharan, 2020). The purpose of the pooling layer is to shrink the image stack into a smaller size. The classification task begins here. In the dropout layer, 0.3 (30%) of neurons are dropped out. The reason to use a dropout layer is when all the features are connected to a fully connected layer it causes overfitting. Overfitting occurs when the classifier works very well on training data, but when new data is fed for classification, it gives negative results. This decreases the overall performance of the model. To avoid this problem, some neurons are dropped out using the dropout layer during the training phase.

The activation function is a parameter of deep neural networks. It performs nonlinearity in the model due to which a model can perform complex tasks. Without an activation function, the deep neural network is a linear regression model. It tells which information is needed to fire and which is not needed to fire. In simple words, it passes out the output from one node to another if that output is necessary for the next node. Because not every output is relevant and equally useful, some can be noise (Gupta, 2020). Some of the widely used activation functions are linear, sigmoid, ReLU, and SoftMax. Every function has its usage. For example, sigmoid is used in binary classification and SoftMax is used in multi-class classification. The schematic diagram of CNN is shown in Fig. 4.

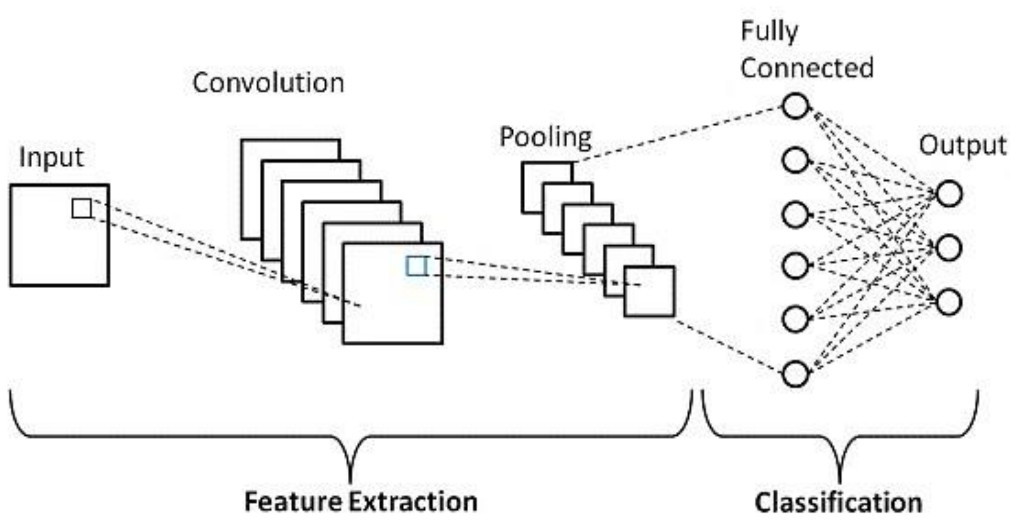

Figure 4: Schematic Diagram of CNN.

3.3.2 Mobilenetv2

MobileNetV2 is a refined version of MobileNetV1 with a smaller number of parameters (Nganga, 2022). It is a type of CNN. The shape of MobileNetV2 is based on depth-wise separable convolutions. It is divided into two phases; depth-wise separable convolutions and pointwise convolutions. This model does not use the ReLU, it uses the linear bottleneck activation function for good feature extraction. It has a smaller number of parameters and a small model size. The residual connection of MobileNetV2 is shown in Fig. 5.

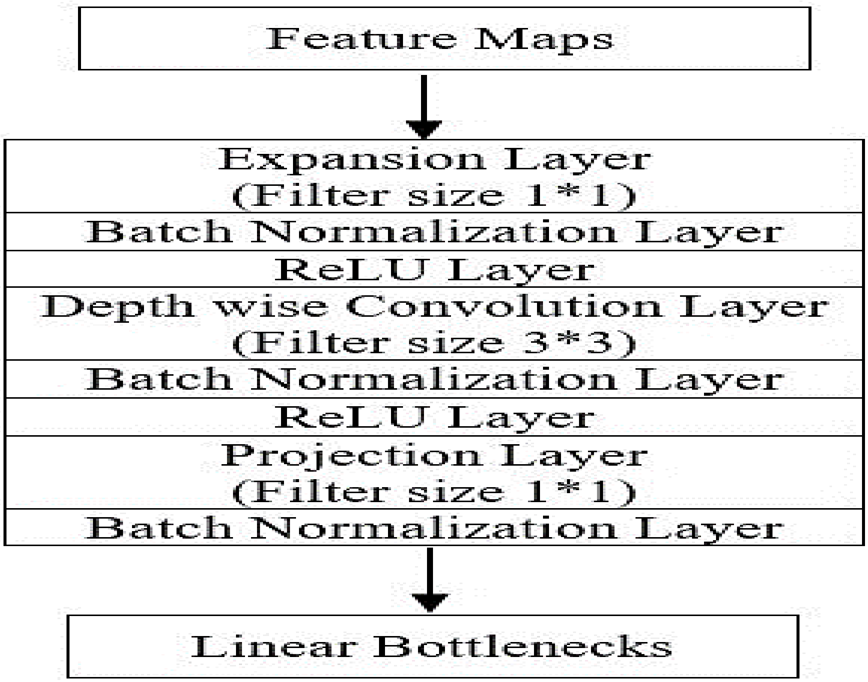

Figure 5: Residual Connections of Mobile NetV2.

4. Proposed Rice Leaf Diseases Classification Model

We proposed a neural network using MobileNetV2 as a base model. The fundamental reason to use MobileNetV2 as a base model is that the residual connections are provided straight to the earlier layers. This fixes the vanishing gradient problem, and degradation issues and avoids squashing of the derivatives, resulting in a higher overall derivative of the block. Weights of MobileNetV2 were loaded from Keras API for feature extraction of rice leaf diseases. There was no classification layer on top. Weights were transferred using the transfer learning technique to transfer the common knowledge from MobileNetV2 to the proposed classification model.

4.1 Base Model Architecture

The base model in our proposed model contained 2,257,984 parameters and residual connections with bottleneck features. It used depth-wise separable convolutions to filter the features of datasets. The detailed architecture of the base model is given in Table 2.

Table 2: Detailed Architecture of the Base Model.

No	Input	Operator	Expansion Factor	Number of Output Channels	Number of Iterations	Stride
1	224^2 x 3	Convolutional2D Layer	_	32	1	2
2	112^2 x 32	Bottleneck Layer	1	16	1	1
3	112^2 x 16	Bottleneck Layer	6	24	2	2
4	56^2 x 24	Bottleneck Layer	6	32	3	2
5	28^2 x 32	Bottleneck Layer	6	64	4	2
6	28^2 x 64	Bottleneck Layer	6	96	3	1
7	14^2 x 96	Bottleneck Layer	6	160	3	2
8	7^2 x 160	Bottleneck Layer	6	320	1	1
9	7^2 x 320	Convolutional2D LayerFilter Size (1 x 1)	–	1280	1	1
10	7^2 x 1280	AveragePooling LayerFilter Size (7 x 7)	–	–	1	–
11	1 x 1 x k	Convolutional2D LayerFilter Size (1 x 1)	–	Kernel	–	–

The purpose of the feature extractor was to convert images into feature blocks. The model took the input image of size 160x160x3. The feature extractor converted the 160x160x3 to 5x5x1280. In the last step convolutional base was created. Freeze this layer so that the weights don't update during the training phase by using base_model. trainable=FALSE. After this step, batch normalization never changes its mean and variance. The inference mode of batch normalization is utilized in this layer.

The proposed classifier used a two-dimensional global average pooling layer with 5*5 spatial locations. This layer generated 1280 vector elements per image. The conversion into this vector occurs from features. To convert features into a single prediction for one image keras dense layer was used. An activation function was not needed as the prediction value is working as the inverse of the standard logistic function. The architecture of the proposed classifier is shown in Fig. 6.

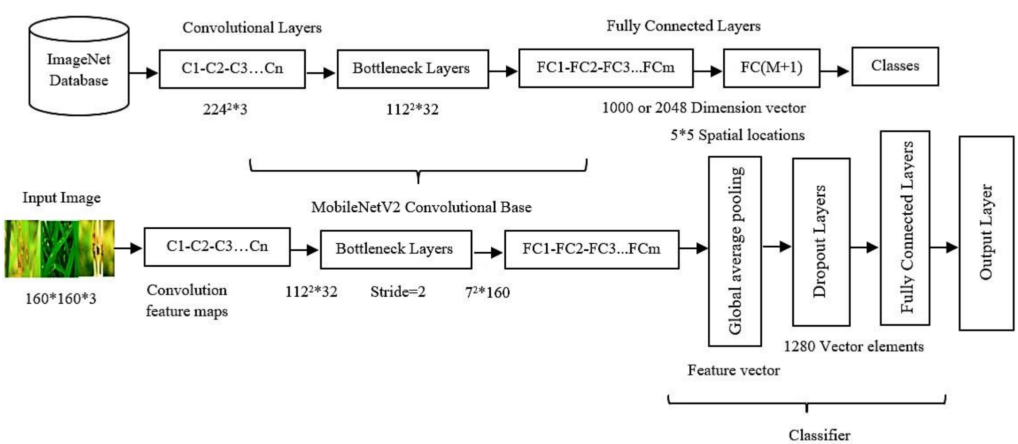

Figure 6: Architecture of the Proposed Model.

Model parameters' arrangement accepts not only carefully selected data but also accepts different kinds of data. This feature does not allow model overfitting. It yielded the best accuracy on the test dataset. A brief description of the rice leaf diseases classification model summary is given in Table 3. Input layers, output from each layer, and the number of parameters is mentioned in this table.

Table 3: Layer-wise configuration of the proposed model

No	Layer (type)	Output Shape	Param Numbers
1	Input Layer	[(None, 160, 160, 3)]	0
2	sequential (Sequential)	(None, 160, 160, 3)	0
3	tf. math. truediv (TF Op Lambda)	(None, 160, 160, 3)	0
4	tf. math. subtract (TF Op Lambda)	(None, 160, 160, 3)	0
5	mobilenetv2_1.00_160 (Functional)	(None, 5, 5, 1280)	2257984
6	global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
7	dropout (Dropout)	(None, 1280)	0
8	dense (Dense)	(None, 7)	8967
	Total params: 2,266,951Trainable params: 8,967 and non-trainable params: 2,257,984		

The proposed model was built by the combination of data augmentation, rescaling images, base model building, and feature extraction with the help of Keras functional API. The parameters of the model were fixed for the training phase. Table 4 shows the values of the hyperparameters.

Table 4: Values of hyper-parameters

No	Parameters	Values
1	Base learning rate	0.001
2	Optimizer	Adam
3	Learning rate	Base learning rate
4	Loss	Sparse categorical cross entropy
5	Logits	True

A pre-trained model was used to eliminate undesirable layers in the proposed classifier. It used layers customized to our dataset and classification task. The model uses keras sparse categorical cross-entropy for multi-class classification and inverse of the standard logistic function.

5 Results

5.1 Experimental Setup

Python programming language was used for preprocessing of the datasets. Datasets were preprocessed for rescaling and augmentation. Keras API was used with the tensor flow backend. All experiments were performed on Visual Studio Code 3.9.10 64-bit (Windows Store) version. MobileNetV2 was used as a base model. Transfer learning was used to transfer weights on the Adam optimizer. The number of epochs used were 20-30. Python programming language was used to check several batches in the validation dataset and then randomly moved 20% for testing.

Multiple experiments were conducted by combining the datasets to check the efficiency and generalization of MobileNetV2. MobileNetV2 performed well even on small datasets with a different number of classes. The model learned to extract meaningful features that were relevant to the task at hand, regardless of any specific dataset. Details for combining the datasets for multiple experiments are given in Table 5.

Table 5: Details of Various Experiments by Combining the Carefully Selected Datasets.

No	Dataset Combination	Classes	No. of Images in Each Class (Training Set)	No. of images in Each Class (Testing Set)	Total No. of Images
1	A+B	Bacterial Leaf Blight Brown Spot Leaf Blast Leaf Smut	13411312104020	33632826020	4,657
2	A+C	Bacterial Leaf Blight Brown Spot Healthy Hispa Leaf Blast Leaf Smut	2045041841841820	2011310510510520	2212
3	A+D	Bacterial Leaf Blight Brown Spot Leaf Blast Leaf Smut Tungro	129913121152201046	32532828820262	6,052
4	B+C	Bacterial Leaf Blight Brown Spot Healthy Hispa Leaf Blast	130916984184181458	328425105105365	6629
5	B+D	Bacterial Leaf Blight Brown Spot Leaf Blast Tungro	2576256021921046	645640548262	10469
6	C+D	Bacterial Leaf Blight Brown Spot Healthy Hispa Leaf Blast Tungro	1267169841841815701046	317425105105393262	8024

5.2 Performance Metrics

The performance of the proposed model was evaluated using four performance metrics; accuracy, precision, recall/sensitivity/hit rate, and F1-Score. Accuracy is the most common measure to evaluate the performance of a classification algorithm. The ratio of correctly predicted positives to the number of all predicted positives is known as precision. The ratio of the total number of positive samples to the number of positive samples that are accurately identified as positives is known as recall/sensitivity/hit rate. A weighted average of precision and recall is known as F1-Score. It is a harmonic mean of both. Eq. (4), (5), (6) and (7) shows the formulas of these metrics.

Accuracy= TP+TN/TP+TN+FP+FN. (4)
Precision=TP/TP+FP. (5)
Recall=TP/TP+FN. (6)
F1 Score=2TP/2TP+FP+FN. (7)

TP stands for true positive; TN stands for true negative; FP stands for false positive and FN stands for false negative. TP is the number of positive images which are truly labeled as rice leaf disease images by the classifier. TN is the number of negative images which are truly labeled as not rice leaf disease images by the classifier. FP is the number of positive images which are falsely labeled as rice leaf disease images by the classifier. FN is the number of negative images which are falsely labeled as not rice leaf disease images by the classifier.

Dataset B is larger than the dataset A but it contains carefully selected images. Dataset C contains noisy images. Dataset D contains more classes as compared to the rest of the datasets but the dataset is carefully selected. Dataset E contains maximum classes as compared to Dataset A, Dataset B, Dataset C, and Dataset D. Every class of this dataset contains a large number of images. Data is not carefully selected, so it trained the classifier for maximum variation in test images. The model is trained on a large dataset so that model does not come across with overfitting. The proposed model is experimented with and compared with other deep neural networks. The results obtained by all experiments are given in Table 6. The accuracy, precision, recall, and F1 score of dataset E with the proposed model is better than the other models. T6 gives better results as compared to others. It is based on mobilenetV2 and uses pre-trained weights. The proposed model did not take much time for training due to transfer learning. Training and validation accuracy and loss are shown in Fig. 7 and Fig. 8 respectively.

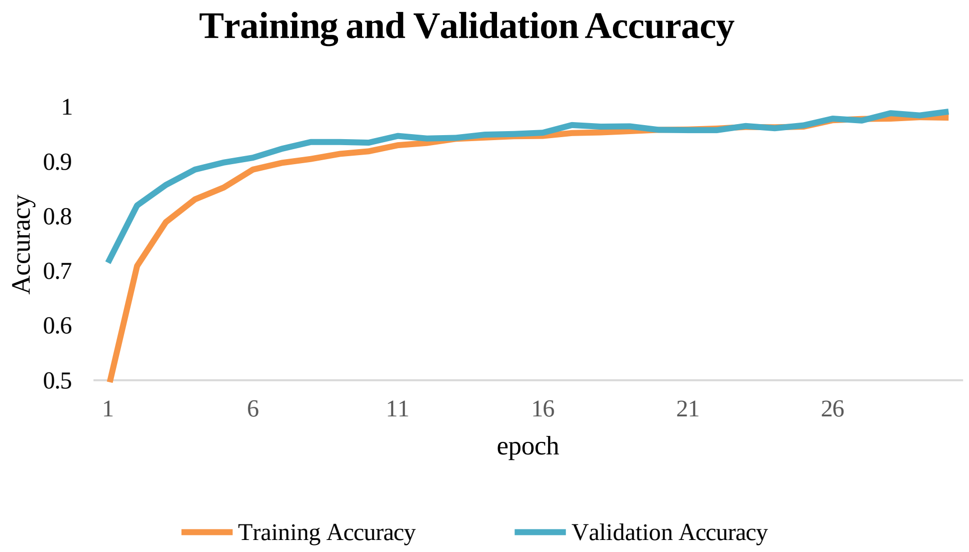

Figure 7: Training and Validation Accuracy of Dataset E Using the Proposed Model.

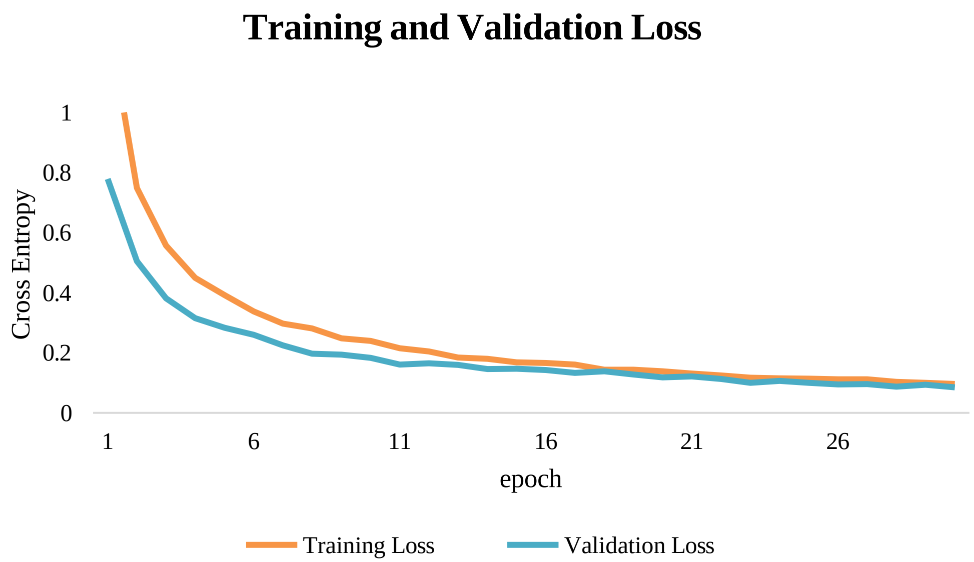

Figure 8: Training and Validation Loss of Dataset E Using the Propose.

Table 6: Comparison of Results Achieved Using Different Experiments.

No	Experiment Number	Dataset Name	Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	T1	Dataset A	InceptionResNetV2	30.00	29.32	30	29.56
		Dataset B		90.37	90.35	90.24	90.21
		Dataset C		55.34	54.62	54.77	54.09
		Dataset D		92.21	91.81	91.58	91.59
		Dataset E		93.93	93.05	93.00	93.02
2	T2	Dataset A	VGG16	31.67	27.46	28.33	26.84
		Dataset B		85.83	85.85	85.82	85.70
		Dataset C		36.52	39.14	36.79	36.75
		Dataset D		88.79	88.95	88.78	88.79
		Dataset E		89.19	88.81	88.76	88.73
3	T3	Dataset A	VGG19	28.33	37.63	28.33	24.41
		Dataset B		85.16	85.65	85.69	85.59
		Dataset C		42.13	40.55	41.29	40.41
		Dataset D		89.30	89.52	89.51	89.50
		Dataset E		90.02	90.15	90.09	90.09
4	T4	Dataset A	Xception	41.67	41.37	41.66	41.51
		Dataset B		91.31	91.16	91.04	91.03
		Dataset C		50.84	50.58	49.43	49.05
		Dataset D		92.52	92.61	92.52	92.53
		Dataset E		93.26	93.19	93.09	93.10
5	T5	Dataset A	MobileNetV2	51.67	43.45	46.66	44.34
		Dataset B		91.84	92.44	92.37	92.39
		Dataset C		45.79	47.26	46.34	46.16
		Dataset D		94.64	94.97	94.95	94.94
		Dataset E		95.43	95.48	95.42	95.43
6	T6	Dataset A	Proposed	58.33	60.29	58.33	55.44
		Dataset B		98.40	97.26	97.19	97.19
		Dataset C		58.15	56.39	54.77	55.18
		Dataset D		98.65	97.94	97.92	97.91
		Dataset E		99.17	98.34	98.33	98.33

Results of different experiments illustrated that MobileNetV2 performed well on various datasets. MobileNetV2 used depth wise separable convolutions, inverted residuals, linear bottlenecks with efficient use of resources. A literature review also showed that researchers and practitioners prefer to use MobileNetV2 over other deep learning architectures because it is an open-source architecture and optimized for low-latency and high-throughput inference, making it ideal for real-time applications. Our proposed model used MobileNetV2 which is lightweight and computationally efficient as a baseline model for rice leaf disease classification. Table 7 shows the outstanding result of the proposed model with various datasets independently and with combinations.

Table 7: Comparison of Results Achieved Using the Proposed Model with Mobilenetv2 on Dataset Combinations.

No	Dataset Name	Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	Dataset A + Dataset B	MobileNetV2	90.03	90.02	90.29	89.90
		Proposed	96.14	94.86	96.14	95.49
2	Dataset A + Dataset C	MobileNetV2	49.73	52.71	50.80	49.58
		Proposed	58.33	60.19	56.72	55.60
3	Dataset A + Dataset D	MobileNetV2	93.49	92.71	93.09	92.80
		Proposed	96.80	95.25	96.09	95.49
4	Dataset B + Dataset C	MobileNetV2	79.82	80.30	79.72	79.94
		Proposed	84.09	82.56	83.36	82.20
5	Dataset B + Dataset D	MobileNetV2	92.04	92.45	92.46	92.31
		Proposed	98.17	98.64	98.63	98.63
6	Dataset C + Dataset D	MobileNetV2	82.98	83.51	83.06	82.97
		Proposed	86.79	89.25	86.40	85.22

6. Discussion

Various researchers have used deep learning-based methods for the classification of plant leaf diseases. CNNs are the most popular among these methods. CNN methods classify diseases with and without transfer learning. The results are exceptional because of the elimination of subjectivity as a result of the automation of plant leaf disease classification. It saves time, especially for large-scale operations in agriculture, where manual inspection and diagnosis of plant diseases could be time-consuming and error-prone. Many researchers suggested that CNN-based approaches have the potential to be used as a practical tool for plant disease diagnosis and management. They performed leaf disease identification and classification using CNN. The research is still evolving in the field. A detailed comparison of results obtained by the proposed model with other studies for rice leaf is done. The comparison is based on accuracy, number of classes, dataset size, and number of parameters used for classification.

AlexNet with transfer learning can provide significant benefits in terms of time, accuracy, and generalization (Atole & Park, 2018) used AlexNet with a stochastic gradient descent approach on three rice diseases (black bug, tungro, and golden apple snails) to estimate the gradient vector. This method used a dataset of 600 images and achieved 91.23% accuracy. Various CNN models AlexNet, GoogLeNet, ResNet-50, InceptionV3, ShuffleNet, and MobileNet-v2 were used by (Pereira, 2019) to check the performance for rice leaf disease classification. MobileNetV2 which is a highly efficient and versatile neural network that is well-suited for mobile and embedded systems performed well. The dataset used in this method contained 2092 images of brown spot, healthy, hispa, and leaf blast and achieved 62.5% accuracy on the test dataset. Shrivastava, Pradhan et al. used AlexNet for feature extraction from rice leaf blast, bacterial leaf blight, sheath blight, and healthy leaves (Shrivastava et al.,2019). Support vector machine was used for classification and achieved 91.37% accuracy while the dataset size comprised 619 images. This study (Shrivastava & Baranidharan, 2020) used transfer learning with a pre-trained CNN model, ResNet50 to classify bacterial leaf blight, brown spot, and leaf smut of rice leaf diseases and achieved 66.67% accuracy. The dataset used to train this model contained 120 images. Rasjava, Sugiyarto et al. aimed to classify brown spot, leaf smut, and bacterial leaf blight rice leaf diseases using a CNN-based approach (Rasjava et al., 2020). The authors achieved an accuracy of 86.67% on the dataset containing 90 images. Masood, Saim et al. suggested localized classification for each image segment which was based on Mask RCNN (Masood et al., 2020). This approach identified the location and extent of diseased areas on the rice crop. This method utilized a dataset containing 1700 healthy and diseased images to attain an accuracy of 87.6%. AlexNet with transfer learning was used to classify bacterial leaf blight, brown spot, and leaf smut and accuracy reached up to 84% (Rao et al., 2020). Ahmed, Rahman et al. used CNN CNN-based dual-phase method on a 200-image dataset containing three classes; false smut, healthy and neck blast, and attained 88.92 % accuracy (Ahmed et al., 2020). Ghosal and Sarkar collected dataset containing rice leaf blast, bacterial leaf blight, brown spot, and healthy classes (Ghosal & Sarkar, 2020). Further, they used a CNN to classify these diseases with an accuracy of 92.46%. The model used transfer learning to fine-tune the pre-trained VGG16 model.

Several CNN models have been proposed to address the challenges of image classification. Purbasari, Rahmat et al. classified leaf blast, brown spot, bacterial leaf blight, and tungro rice diseases with an accuracy of 51.2% (Purbasari et al.,2021). The model was trained on the dataset of 2239 images and used the CNN model. To develop and evaluate deep learning algorithms for rice disease classification Krishnamoorthy and Parameswari assessed VGG-16, ResNet50, and InceptionV3 for rice leaf disease classification and achieved accuracies of 87%, 93%and 95% respectively (Krishnamoorthy & Parameswari, 2021). This study used a dataset of 5200 color images of 3 disease categories namely leaf blast, brown spot, and bacterial blight as well as the images from the healthy category. Researchers used a small size of data which is representative of the task and achieved different accuracies. Islam, Shuvo et al. used transfer learning with four pre-trained CNN models (VGG-19, Inception-Resnet-V2, ResNet-101, and Xception) to classify brown spot, leaf blast, bacterial leaf blight, leaf smut, and healthy paddy leaf disease (Islam et al., 2021). Their confined dataset of 984 images helped achieve maximum accuracy of 92.68% using Inception-Resnet-V2. Zhou Hui used the rice leaf tip, healthy rice, arthritis, chronic leaf blast, and bacterial streak classes and trained the classifier on 500 images using CNN and attained 95.5% accuracy (Zhou et al., 2021). CNN architecture-based classification was performed by Su, Hung et al. using the data size of 120 images of bacterial leaf blight, rice brown spot, and leaf smut classes and accomplished 81.25% accuracy (Su et al., 2022). Upadhyay applied DenseNet121 on 240 images comprising the fungus-caused leaf blast, bacteria-caused bacterial leaf blight, and virus-caused tungro rice leaf diseases to achieve an accuracy of 96.09 % (Upadhyay, 2022). CNN with transfer learning was used by Costales, Callejo-Arruejo et al. for the classification of leaf blast, brown spot, and hispa rice leaf diseases (Costales et al., 2023). The size of the dataset was 1260 images and the model was fine-tuned using a pre-trained network on ImageNet. This method achieved an exceptional accuracy of 98% on the test set.

The proposed approach collected a higher number of images and prepared a large size dataset of 7445 images. It helped to improve the accuracy of the classifier. This provided much data that is a better representative sample of the population. It also allowed the model to learn a more accurate representation of the underlying patterns in the data with discriminative and informative features. The proposed method also contained five classes namely bacterial leaf blight, leaf blast, brown spot, hispa, and tungro. Our model performed better in terms of accuracy, large data size, and the number of diseases as compared to the previous models (a work of almost sixteen latest researches has been used for comparison).

The research has unveiled that a model with too many parameters can memorize the training data instead of learning the general underlying patterns. It may lead to overfitting, where the model performs well on the training data but poorly on new, unseen data. This can limit the model's usefulness in real-world applications. They require more computational resources (such as memory and processing power) and time, which is expensive and time-consuming. In the proposed research five pre-trained CNN models; Xception, VGG16, VGG19, InceptionResNetV2, and MobileNetV2 were applied to all datasets. These datasets contained different characteristics. MobileNetV2 gave the highest accuracy among all deep learning models. Therefore, we have proposed a method in which MobileNetV2 is used as a base model with transfer learning to make it efficient in terms of both model size and computation. It achieved the desired results by using a combination of depth-wise separable convolutions and linear bottleneck layers, that helped to reduce the number of parameters in the model. It also reduced the computational cost of each layer making it well-suited for resource-constrained environments such as mobile and embedded devices. Another difference with state of art methods is that all other methods were trained on the small size of data. The proposed classifier was trained on larger and more diverse datasets that improved its generalization.

7. Conclusion

In this paper, we have proposed a deep learning-based rice leaf disease classifier based on pre-trained CNN for the five major devastating and most frequently found rice leaf diseases. The architecture of the proposed model consists of inverted residual blocks with depth-wise separable convolutions and linear bottleneck layers. Five datasets are used for experiments to check the robustness of deep learning classifiers to various forms of noise and perturbations in the data. Three datasets are self-collected and two datasets were downloaded from online resources. We used Xception, VGG16, VGG19, InceptionResNetV2, and MobileNetV2 on these five datasets. Experiments allowed us to optimize the performance of the classifier by identifying the optimal set of parameters that improve the performance of the classifier. We achieved an effective and efficient classifier in terms of high accuracy and a smaller number of parameters with a high number of classes using MobileNetV2 as a baseline model. The results of this study demonstrate the feasibility and potential benefits of utilizing transfer learning with CNN models for crop disease classification by leveraging the knowledge gained from pre-trained models. The proposed model in this research paper achieved high accuracy rates in the classification of bacterial leaf blight, leaf blast, brown spot, hispa, and tungro diseases affecting rice plants. The mean accuracy, precision, recall, and F1 score was approximately 99%. Future work will focus on other rice leaf diseases. Additionally, our proposed methodology can also be experimented with on real-time data of rice leaf diseases in fields. Robots equipped with spraying technology can be programmed through the rice leaf disease classification method to identify and locate the diseased areas, and then apply the appropriate amount of pesticide or fungicide directly to those areas without spraying the entire field or wasting resources. This area According to the real-life environment conditions, the classifier can be modified for high accuracy and also further reduce the number of parameters by network pruning to improve the classification speed.

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