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Detection of Rice Plant Leaves Diseases using Data Augmentation and Transfer Learning Techniques

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Abstract : Rice is considered one of the crops of great importance to people worldwide due to its high nutritional value, and the countries that consume it most are Asia in the first place. However, for decades, farmers and agronomists have had to contend with many persistent agricultural problems, such as various Rice plant leaf diseases . A rapid, automatic, less costly and reliable approach to detecting rice diseases is widely required in agricultural information because severe rice infection may result in non-harvest of grain.

Deep learning study is used for such tasks to get excellent and fast solutions to image problems and reach high accuracy classification. In this paper, we have focused on deep learning. Using the convolutional neural network algorithm, one of the most tested algorithms for its accuracy and flexibility in dealing with different types of classifications, the learning transfer techniques that save a lot of time and effort are bypassed, and we have used more than one type of transfer learning. A data augmentation technique has also been used, which helps to achieve good results. Three sets of databases were used for different rice diseases. We have four categories of diseases, for example (bacterial leaf blight, brown spot, LeafBlast, and Hispa).

The highest accuracy for the first group of data reached (100 %), (97.14%) for the second group, and the result of the third group (100%). As for the data totals after the augmentation process, they are as follows, the first (100%), the second (97.42%) and the third (100%).

1. Introduction

At the global level, many people consume the rice crop, more than half of the world's population, and it is an essential and fundamental food. Quality and productivity are greatly affected by diseases affecting the rice crop [1].

Rice is grown in several regions of the world, namely Asia, Africa, America, Europe and Oceania. Reference to the Food and Agriculture Organization of the United Nations (FAOSTAT) confirmed in their report that the highest production in Asia reached 91.05%, and the percentages are decreasing, as shown in Figure 1 [2].

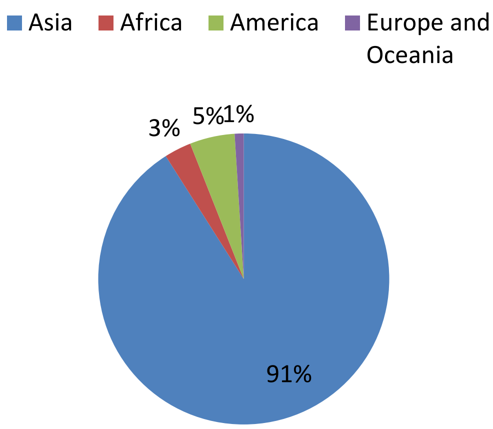


Fig. 1. Production of Rice World (Source FAOSTAT)

By 2025, the World Bank predicts that there will be a 51% increase in demand for rice. Damage to the rice crop in this situation, regardless of the cause, is unacceptable[3] .

One of the advantages of automatic diagnosis of plant diseases is accuracy in detection and speed, which results in the development of agriculture. Even an agriculturist and pathologist may frequently fail to recognize the illnesses in plants by observing diseased leaves due to the cultivation of a vast range of crop items. Visual inspection is still the main method of disease detection in rural parts of poor nations, nevertheless. Experts must also continuously monitor it. Farmers in outlying places might have to make an expensive and time-consuming trip to an expert's office. With their high throughput and accuracy, automated computational systems for plant disease detection and diagnosis benefit farmers and agronomists[4].

On the other hand, the most promising method to automatically learn important and discriminative features is based on deep learning-based technologies, particularly CNNs[5]. Various convolutional layers make up deep learning (DL), which represents learning features from the data. Deep learning a model can be used to identify plant diseases. Deep learning has some disadvantages as well because it needs a lot of data to train the network. When there are not enough photos in the data collection, performance suffers. There are many benefits to learning by conversion, such as the fact that network training does not require a significant amount of data. By applying knowledge from a previously acquired, analogous task to the current activity at hand, transitional learning enhances learning. Translational learning has been applied in illness discovery methodologies in several studies [6]. Using files for transfer learning has the advantages of cutting down on training time, generalization error, and DL model construction costs [7]. To identify the plant diseases in this study, we employ various DL models. The initial module can extract more precise and pertinent information since it can extract multiple levels of features at once .Many models were employed (InceptionResNetV2, densnet201, mobilenetv2, ResNet152V2, EfficientNetB3, and EfficientNetV2L). We tested the performance of the implemented DL architecture using various batch sizes. Performance was also evaluated using values and learning rates. Evaluation results demonstrated that CNN's deep implementation was successful.

Popular classifiers include the K-nearest neighbor (KNN) algorithm [8], the support vector machine (SVM) algorithm [9], the decision tree, the random forest (RF) algorithm [10], the naive Bayes algorithm [11], the logistic regression algorithm [12], the rule generation algorithm [13],They are all used to solve classification and detection problems in artificial intelligence.

learning methods. These are the paper's primary contributions: A variety of convolution neural network (CNN) architectures, including Resnet152, DenseNets121,mobilenetv2, InceptionResNetV2 , EfficientNetB3, and EfficientNetV2L,are used to detect plant illnesses using photos of healthy and diseased leaves.transfer-learning-based CNN was implemented. We eliminated all layers from each

model after the fully linked layer, freezing the layer weight before it. An activation layer, a batch-normalization layer, and a dense layer were added as a stack. We employed a dropout layer with various dropout values after each batch-normalization layer to avoid the architecture from overfitting. It has a large number of features. Therefore, we have implemented the techniques of organization in the dense layer for each model, which facilitated the model. For best results, we have fine-tuning the network parameters. We modified various parameters and tested them extensively. We used different batch sizes between 5 and 15, and the dropout rate was 0.4. We evaluated the model with learning rates of 0.1 in order to improve it. Different eras were used to train the models[14][15][16].
A data augmentation technique was used to increase the number of images in each class.The number of databases that are used in this study are three groups, the first contains 120 images, the second contains 2092, and the third is 5932.
The ability of artificial intelligence to develop solutions for rapid and reliable detection of diseases. Currently, in developed countries, the management of crops, pests and diseases, soil irrigation and storage control is highly dependent on artificial intelligence [17] .
The development of systems with artificial intelligence constitutes an important difference in the form of the general development of life in terms of accuracy, cost and ease of dealing[18][19]

2.Related works
To automatically detect rice leaf diseases using deep learning techniques, there are limited publications while we compare them with other plant diseases. Previous studies and methods adopted by the authors in their areas of research will be illustrated.
In recent research, the approach of transfer learning has been utilized widely as a training method for model classifications. Ghosal et al [20] conducted a study in which they employed a structural framework that was particularly focused on the VGG-16 classification of diseases that can affect rice leaves. In other words, Shrivastava et al [21] use a pre-trained AlexNet A model in conjunction with an SVM classifier. This is an example of identical strategic phrases. Hassan et al[22] utilized an SVM classifier in a similar way when adopting a suggested deep model for CNN. Atul et al[23] Transportation I became familiar with an architecture based on AlexNet and used a little bit of Exact parameters . ResNet50 user, and DenseNet169 models were used in Mathulaprangsan et alstudy 's [24], which involved a comparison of different models. The incorporation of architectures v3, MobileNet-v1, and Resnet50 is beneficial to Kamrul et al[25]. Sethi et al [26] Use eleven transfer learning networks with the SVM classifier to extract deeper features.
They employed the Inception-v3 structure, and the final layers were retrained using rice disease data sets [27]. Adding some changes, Mickey et al. Chen et al. It was suggested by DENS-INCEP that Al Qaeda combine their DenseNet Model 201 [28]. Transmission models with precisely tuned transmissions, like the VGG16 and Inception V3, were evaluated by Rahman and colleagues, who contrasted those models with those of a The building, which would be comprised of two stages [29]. Bhattacharya and others, For the second stage, he suggested using a CNN model with particular features a strategy for predicting diseases that affect rice ,There is an classification of heath leave and sick leave when the sickness is in its early stages. The second to three categorical categories of rice diseases follows after this[30].
Sharma et al. CNN suggested an allocation that categorizes rice leaf diseases into three distinct groups [31]. The assignment involves injecting new structures. Regarding the identical concept, Liang et al. Extraction capabilities tailored to specific needs The SVM classifier was utilized in order to do the evaluation of the architecture [32].
Comparing the SVM-HOG model to the AlexNet model and other models based on VGGNet11, Liu et al[33] came to the following conclusion: Ahmed and the rest of them. Work An technique that consists of two steps and uses Faster-RCNN, the extraction of regions of interest, and the VGG-16 classification network [34]. Chu et al. Integration of R-CNN and FCM-KM should take place more quickly for area of focus as well [35]. Quick comparisons - RCNN, RetinaNet, YOLOv3, and Mask-RCNN is yet another strategy that was developed by Kiratiratanapruk et al[36]. (See Table 1).

Table 1. Comparison of various classification techniques for plant diseases.

Reference	Year	Objective	Methodology	Parametric Measure	Result
[37]	2012	Leaf disease detection	Color extraction	Accuracy	Disease spot accurately detected.
[38]	2017	Detect the classification of leaf disease	K-Mean Clustering	Accuracy	FCM=95% K-Mean=85.05%
[39]	2009	Detection of rice seed disease	Support Vector Machine	Accuracy	97.2%
[40]	2015	Identification of rice panicle	Principal Component Analysis and Support Vector Machine	Accuracy	96.55%
[41]	2018	Rice disease determination	Principal Component Analysis and Neural network	Accuracy of BP neura network	95.83%

2.1. Research and motivation gaps

Few samples available, or unweighted totals of data. The presence of a representative deficiency of some groups resulting from rice diseases and the decrease in the necessary sample for learning models, when compared with the other disease category, does not match. Therefore there is no balanced data set, which results in biased classification outputs. Unitary data sets do not exist. Most of the studies are based on images that are collected manually from the fields. Causing a discrepancy between the study research as a result of the lighting or coloring factor of the image backgrounds and the incorrect comparison of the outputs of the studies conducted without taking these factors into account.

3.Proposed Model

3.1 Rice Plant Leaves Diseases (RPLD) model

The model (RPLD) consists of several stages, as shown in figure 2. The first stage of the (RPLD) architecture is make preprocessing. A non-linear digital filtering method called the median filter is used to reduce image noise. Preprocessing of data is an important part of reducing noise in images to improve them. Intermediate filtering is mainly used for processing and preserving the edges of samples with less distortion. The data augmentation utilizing traditional data augmentation techniques, the benefits, and The models' training data are expanded. Reducing data shortages to enable the creation of better models, reducing overfitting of the data and raising data variability, and reducing the expense of marking and collecting data. The models' increasing capacity for generalization assists in resolving concerns with classification's class imbalance, and the second, The DTL model, is a stage; in the preprocessing step, traditional data augmentation is mainly used, while DTL is mainly used in the benchmarking stage. Six models are used in this study, and they consist of different layers to give results that we can compare and rely on. In these models, we will use transfer-learning technology to retrain the data we have, which gives a short time and excellent results. transfer learning will be adopted as the method of selecting the part of the model to be retrained, which is only the last part of it, thus providing great reliability of the results.

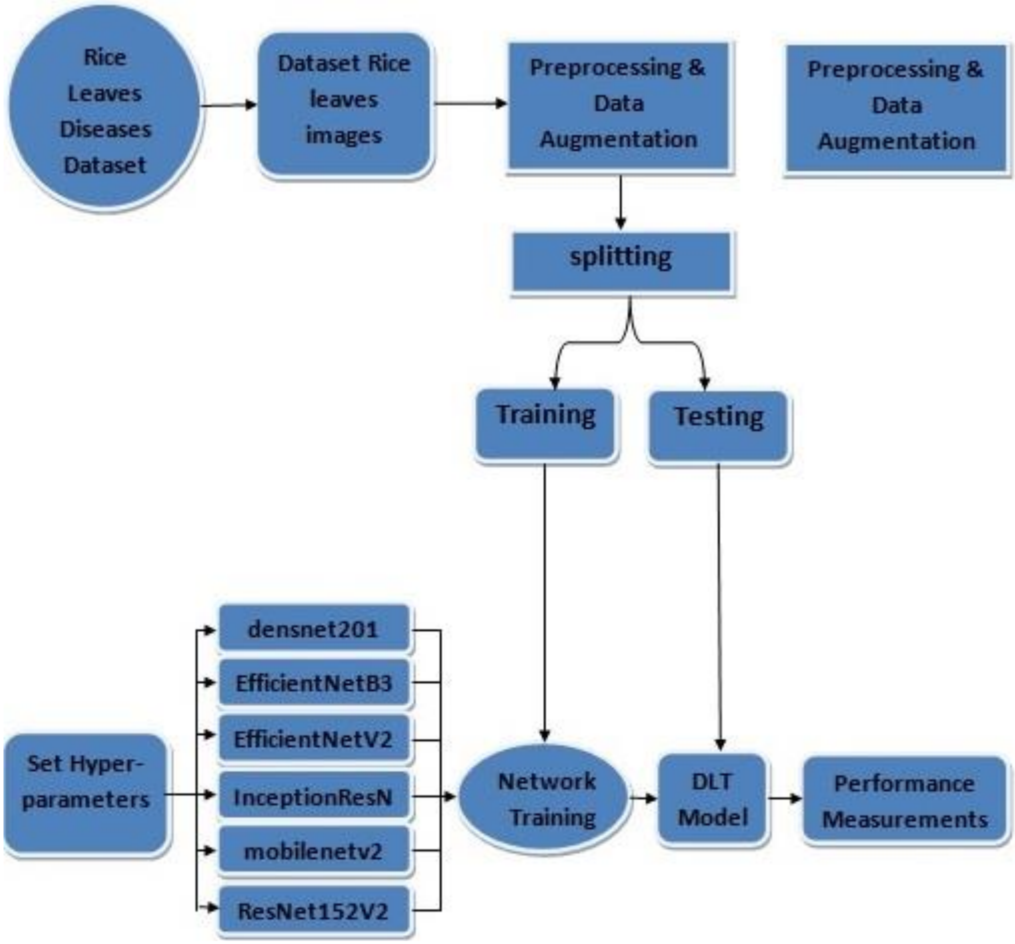


Fig 2. Work-flow Rice Plant Leaves Diseases (RPLD) model.

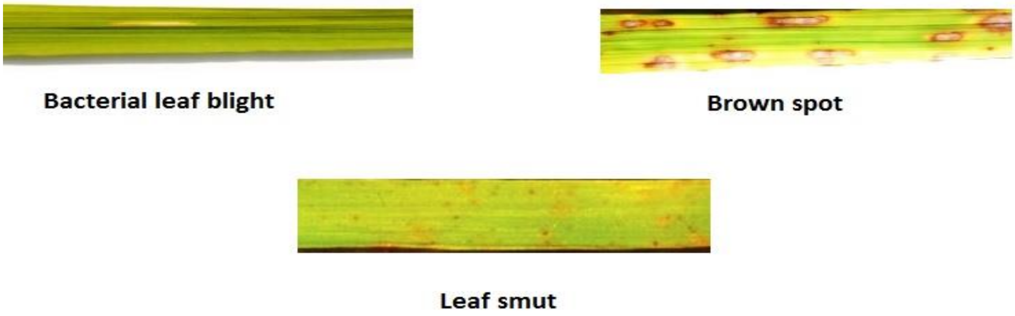
3.2. **Dataset**

In this research, three open-source datasets were used, Table 2, figure 3. The first set consists of three classes of diseases, which are (Bacterial leaf blight, Brown spot, and Leaf smut) and consists of 120 images; the general format of the samples is JPG, the complex overlapping of the background of the images, the visual inconsistency of the samples, or the second database was classified into four diseases, with a total number of images of 2092, with a bad background, but the intensity of lighting is good. The third group consists of four classes (Bacterial blight, Blast, Brownspot, Tungro) and contains 5932 medium-sized background images, and the light intensity is relatively good. These images are first processed uniformly using a field filter and the RGB model for future computations, after which the images are scaled.

Table 2. Rice Plant Leaves Diseases datasets .

Paper	Dataset	Number of Samples	Classes
[42]	Rice Leaf Diseases	120	Bacterial leaf blight, Brown spot, Leaf smut

[43]	Rice Diseases Image Dataset	2092	Brown spot, Hispa, Leaf Blast, Healthy
[44]	Rice Leaf Disease Images	5932	Bacterialblight, Blast, Brownspot, Tungro



Rice Leaf Diseases [35]

Rice Diseases Image Dataset [36]

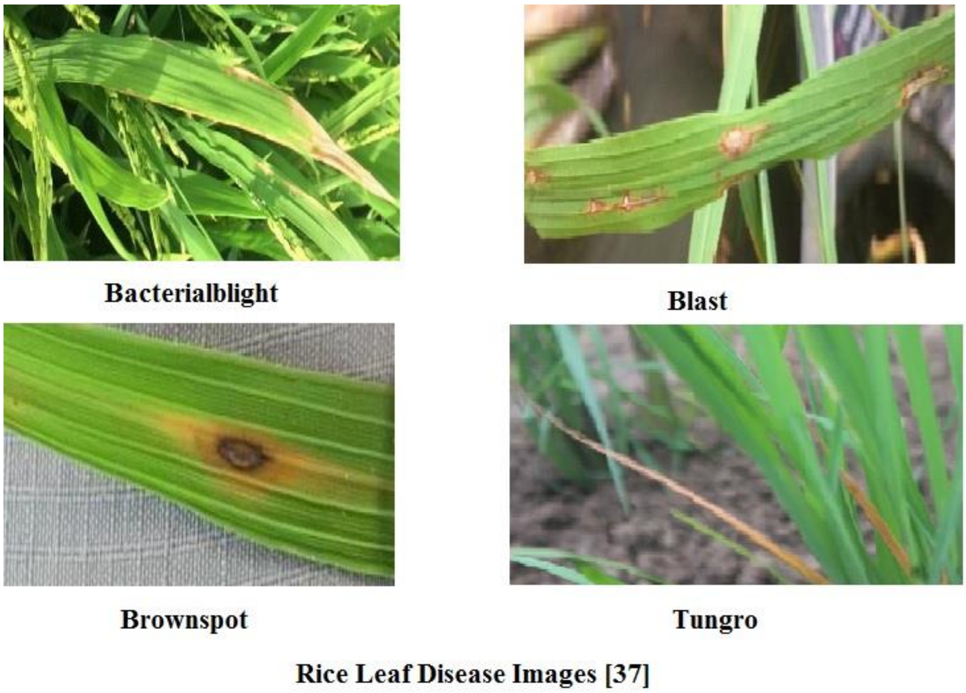


Fig3. . Rice Plant Leaves Diseases datasets .

3.3preprocessing and Enhancement

Image preprocessing is the method used to remove other objects and various noises from an image. One of the most popular ranking stats filters is the median filter because it works well with some specific noise types, including “Gaussian sounds,” “random,” and “salt and pepper.” The median filter replaces the median window value relative to the central pixel of the neighborhood of M in M. Be aware that noise pixels are thought to be significantly different from the average. This type of noise problem can be eliminated by using average filter technology. The image has also been resized for display, storage, and modification. The size of the images has been standardized to 300 x 300 pixels [45]; see figure 4.

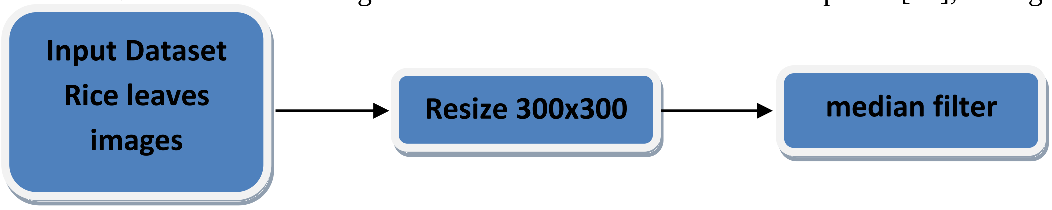


Fig 4. preprocessing Rice Plant Leaves Diseases datasets.

Generate transformations that improve the sham features, and the plan of growing the data amount was used. On the other hand, reducing the total amount was used to implement transformations that improved the visualization of issues relating to imbalanced data sets. At first, it was put into operation with the help of the Albumentations augmentation library for processing data, type of augmentation, and overall operation. Rotation of ninety degrees, When we rotate a point around the origin by ninety degrees anticlockwise, our original point A(x,y) becomes the new point A' (-y,x). To put it another way, swap x & y and get y negative, a Turning Angle of 270 Degrees, When we rotate a point 270 degrees in the counterclockwise direction around the origin, our original point A(x,y) becomes the new point A' (y, -x). This indicates that we swap x and y, make x negative, flip left-right images, and flip top-bottom images [46].Table (3) shows the number of samples after the increase process.

Table 3. Rice Plant Leaves Diseases datasets augmentation.

Paper	Dataset	The total number of samples	Classes
[42]	Rice Leaf Diseases	640	Bacterial leaf blight, Brown spot, Leaf smut
[43]	Rice Diseases Image Dataset	8368	Brown spot, Hispa, Leaf Blast, Healthy
[44]	Rice Leaf Disease Images	22796	Bacterialblight, Blast, Brownspot, Tungro

3.4 Deep Transfer Learning

Classifying images and videos efficiently and efficiently is called Deep Transfer Learning (DTL). A single DTL model consists of numerous convolution and pooling layers that extract features from images and videos and create more intricate deep features in deeper levels, see figure 5. Think of layer l as a combination of layers. Assume we have a convolutional layer that is followed by some N x N square neuron nodes. The output size of the convolutional layer is (N M + 1) x (N M + 1) and will result in k-feature maps if we employ a M x M filter (mask) W. A feature extractor, the convolutional layer extracts features from the inputs. Convolution layer characteristics like edges, lines, and corners are extracted from the image. To determine the unit's pre-nonlinearity input. The input of layer l-1 is then calculated using equation (1):

$$Z_i^l = B_i^l + \sum_{a=1}^{N}\sum_{b=1}^{N} W_i \, X_{(i+a)(j+b)}^{l-1} \quad (1)$$

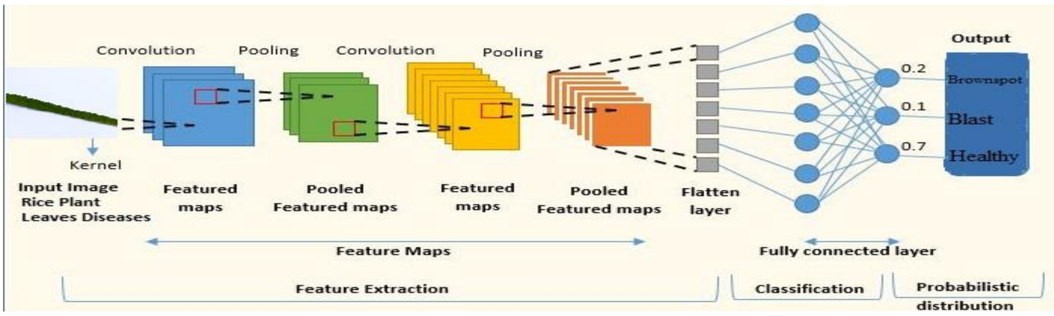


Fig 5.Illustration of the deep convolutional neural network

Convolution and nonlinearity are the two procedures that make up the classic convolutional layer, which is one of these layers. The convolutional layer is also one of these layers. One possible name for the process in question is convolution.

$$X_j^l = \sum_{i=1}^{N} X_i^{l-1} * W_{ij}^{l-1} + b_j^l$$

it was compared to traditional pre-trained architectures.These architectures include VGG19 ,Resnet152v2 , DenseNets121, mobilenetv2, InceptionResNetV2, EfficientNetB3 and EfficientNetV2L [6],[47],[4].Each layer in the base DenseNet model gets input from layers above it before passing its feature-maps to all subsequent layers, producing very deep inputs [48], see figure 6.

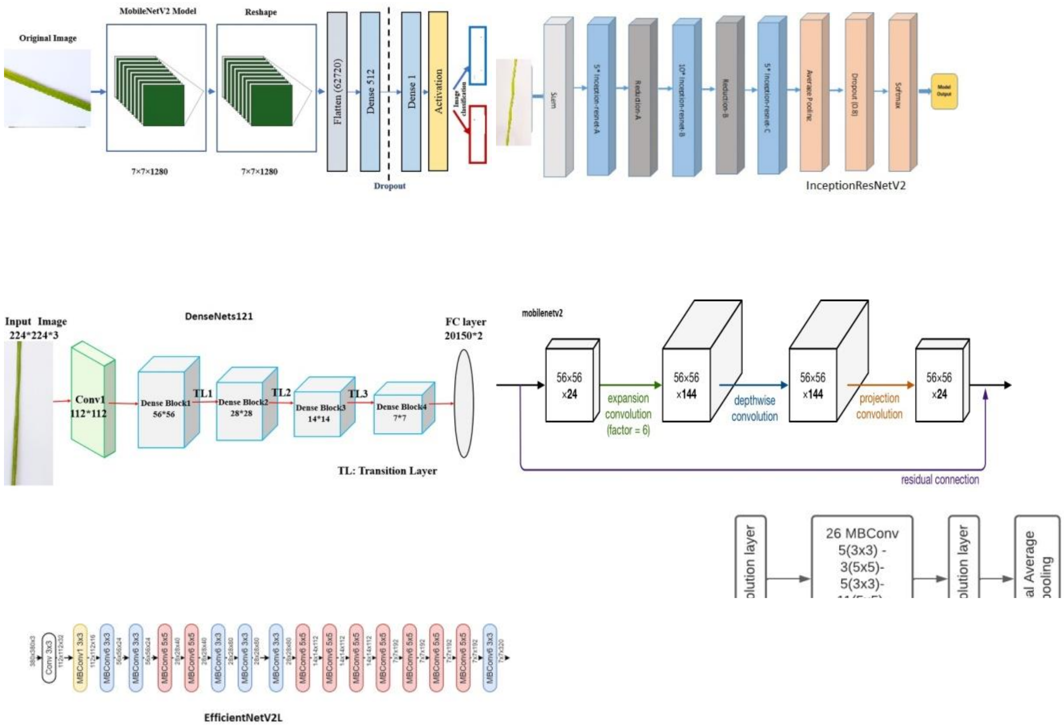


Fig 5.pre-trained architectures models

4. Evaluation technique

The binary classifier is made up of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), using the scale that is represented by the following equations:

$$\text{Accuracy} = \frac{TP + TN}{N}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F} - \text{measure} = 2\,\frac{Precision\,.\,Recall}{\text{Precision}\,.\,\text{Recall}}$$

5. Results and Discussion

5.1. Environmental Setup

The (RPLD) model on Google Colab Has been practiced on a sophisticated graphics processing unit (GPU). The GPU used (NVIDIA Tesla K80) has a CUDA Deep Neural Network (CuDNN) library for GPU learning and has 2304 CUDA cores. Deep learning package consisting of TensorFlow computer vision and Python as a base library, 12GB/16GB GPU memory, and GPU memory clock. The suggested model was evaluated using two different test cases, which are as follows: The first scenario will involve testing DTL models in rice leaf diseases using the initial data set. In contrast, the second scenario will involve increasing the amount of data. In every test trial scenario, diseases belonging to the four groups were included. Based on the breakdown presented in Table 4, each scenario includes verification and testing phases.

Table 4. Configuration of DTL models

Model	Batch size	Momentum	Epoch	Learning Rate	Optimizer
InceptionResNet V2	5-15	0.99	30-200	0.001	Adam
densnet201					
mobilenetv2					
ResNet152V2					
EfficientNetB3					
EfficientNetV2L					

Six DTL models are displayed in Table 3 with initial learning rates (μ) of Start with 0.001 and epoch counts of (30-200). Moreover, a mini-batch size of 5 is selected. Adam [49] is the optimizer technique we have selected to use, and it updates the weights parameters. We take advantage of this issue by utilizing the dropout approach[50] and Appropriate training repetition uses an early stop approach to stop overfitting issues in a deep learning network [51].

5.2. Performance Analysis

Accuracy, F1 score, Precision, and Recall are some variables utilized in this research project to evaluate how effectively the suggested models and other methodologies worked. An illustration of performance measurement is a test's estimated level of accuracy. Additional reflections on the improvement in the accuracy of the test The evaluation of the suggested model has been completed. Each of the three data sets discussed in Section 3.1 was evaluated using models transfer learning models to determine how well our modification fared in comparison to the other models.InceptionResNetV2,densnet201, mobilenetv2, ResNet152V2, EfficientNetB3, and EfficientNetV2L are examples of DTL models. Additionally, there are two scenarios: the first uses the original data from Table 5 and Figure 7 while the second does so after data augmentation from Table 6 and Figure 8.

The rice leaf disease [21] was tested using the first data set, which had the highest accuracy (100%) for the InceptionResNetV2,densnet201, mobilenetv2, EfficientNetB3, and EfficientNetV2L models, and the second data set, which had the highest accuracy (97.14%) for the models EfficientNetB3 and EfficientNetV2L, and the third data set, which had the highest accuracy (100%) for the model densnet201.

Following data augmentation, the first group has the highest accuracy for the InceptionResNetV2 and densnet201 models (100%), the second group has the highest accuracy for the EfficientNetB3 and EfficientNetV2L models (97.42%), and the third group has the highest accuracy for the InceptionResNetV2 model (100%). These results have given higher accuracy than the studies discussed in Section 2 of this article.

Table 5. DTL testing accuracy With Original Data.

Dataset used	Model	Accuracy%	Precision	Recall	F1 score
Rice Leaf Diseases [35]	InceptionResNetV2	100	100	100	100
	densnet201	100	100	100	100
	mobilenetv2	100	100	100	100
	ResNet152V2	0.875	0.9167	0.8750	0.8667
	EfficientNetB3	100	100	100	100
	EfficientNetV2L	100	100	100	100
Rice Diseases Image	InceptionResNetV2	0.9545	0.9423	0.9424	0.9615
	densnet201	0.9619	0.9637	0.9619	0.9621

Dataset	mobilenetv2	0.9333	0.9385	0.9330	0.9322
[36]	ResNet152V2	0.9524	0.9609	0.9519	0.9522
	EfficientNetB3	0.9714	0.9750	0.9712	0.9715
	EfficientNetV2L	0.9714	0.9721	0.9715	0.9717
	InceptionResNetV2	0.9899	0.9900	0.9906	0.9901
Rice Leaf	densnet201	100	100	100	100
Diseases	mobilenetv2	0.9798	0.9793	0.9812	0.9800
[37]	ResNet152V2	0.9933	0.9932	0.9938	0.9934
	EfficientNetB3	0.9731	0.9743	0.9736	0.9739
	EfficientNetV2L	0.9798	0.9811	0.9802	0.9805

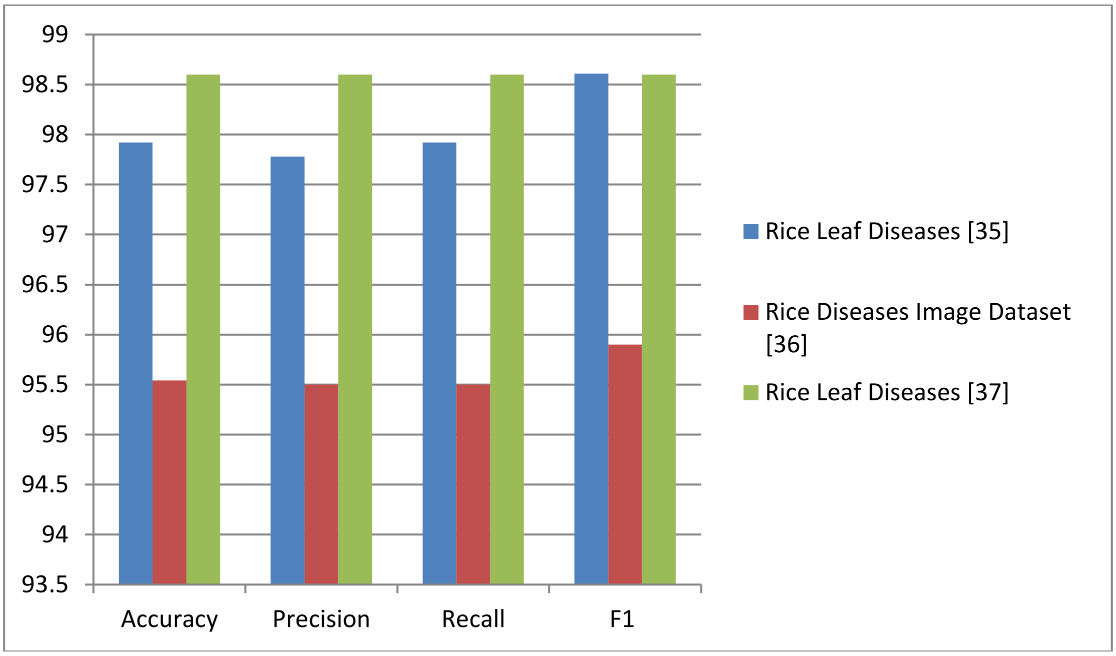


Fig 7. Comparison of average results on all 3 datasets used.

Table 6. DTL testing accuracy with data augmentation.

Dataset used	Model	Accuracy%	Precision	Recall	F1 score
	InceptionResNetV2	100	100	100	100
Rice Leaf	densnet201	100	100	100	100
Diseases	mobilenetv2	0.9688	0.9722	0.9688	0.9686
[35]	ResNet152V2	0.9688	0.9722	0.9688	0.9686
	EfficientNetB3	0.9688	0.9722	0.9688	0.9686
	EfficientNetV2L	0.9688	0.9722	0.9688	0.9686
Rice	InceptionResNetV2	0.9513	0.9510	0.9510	0.9507
Diseases	densnet201	0.9618	0.9617	0.9617	0.9617
Image	mobilenetv2	0.9475	0.9494	0.9475	0.9471
Dataset	ResNet152V2	0.9002	0.9083	0.9013	0.8993
[36]	EfficientNetB3	0.9642	0.9639	0.9641	0.9639
	EfficientNetV2L	0.9642	0.9642	0.9641	0.9641
Rice Leaf					
Diseases	InceptionResNetV2	0.9991	0.9991	0.9991	0.9991

[37]	densnet201	0.9982	0.9983	0.9984	0.9983
	mobilenetv2	0.9991	0.9991	0.9991	0.9991
	ResNet152V2	0.9912	0.9914	0.9913	0.9913
	EfficientNetB3	0.9982	0.9982	0.9982	0.9982
	EfficientNetV2L	0.9974	0.9974	0.9974	0.9974

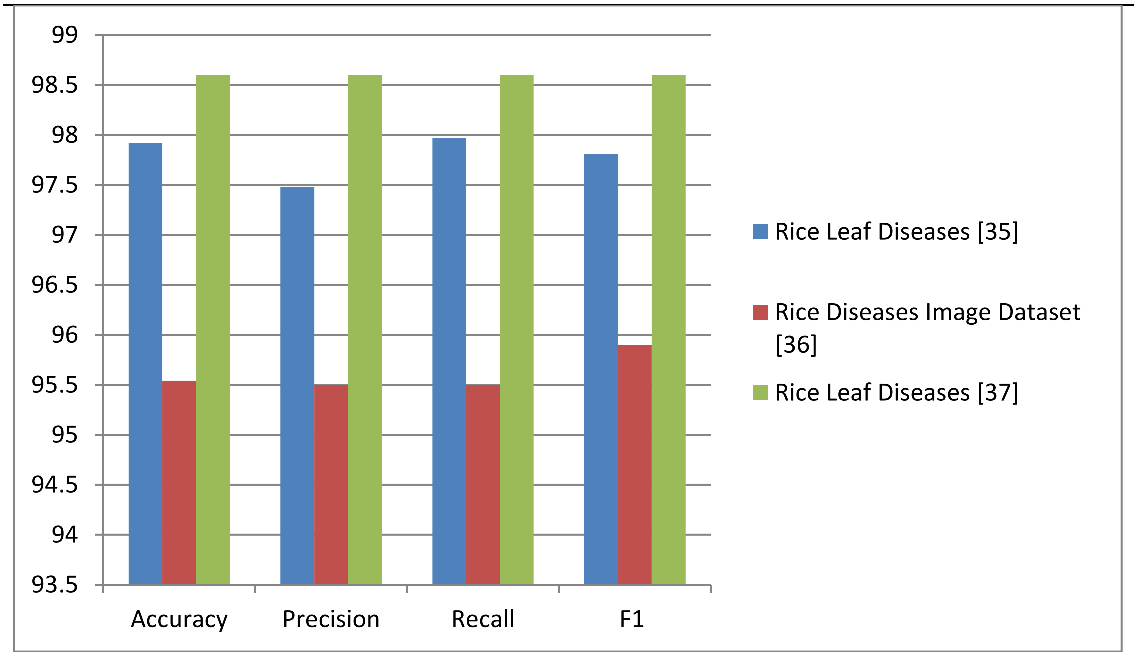


Fig 8. Comparison of average results with augmentation on all 3 datasets used.

5. Conclusion

The model (**RPLD**) for rice disease detection can be very beneficial to farmers and agricultural organizations. This study tested multiple models for rapid and accurate classification of rice diseases. We relied on databases to evaluate the proposal in terms of effectiveness, as it amounted to three data sets with various sample sizes and several classification models. Due to the very low image quality of the rice disease image data set. In addition, six deep transfer learning models were used in this work for analysis (InceptionResNetV2, densnet201, mobilenetv2, ResNet152V2, EfficientNetB3, and EfficientNetV2L). Increasing data and integrating it with deep learning improves accuracy, and performance measures, which include sensitivity, specificity, accuracy, and F1 score, are improved by combining traditional data augmentation with deep transfer learning. The model has fewer layers than other conventional models, but we may get excellent precision thanks to the number of epochs and methods of improvement. It will be simpler for farmers to secure their crops if we can detect the virus.

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