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A Comparative Study of Two Convolutional Neural Network Models for Detecting Rice Plant Diseases Using Online and Local Image Data

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ABSTRACT

Rice is one of the most widely staple foods around the globe, however, rice fields are severely affected by diseases, which can disrupt global food security. Early and accurate detection of rice diseases is essential for the recovery of such rice plants. Manually identifying rice plant diseases can be tedious and error prone. Artificial intelligence (AI) driven models, such as Convolutional Neural Networks (CNN) have proven very successful in the identification or detection of various crop diseases. This study, therefore, presents a comparative study of the effectiveness of two popular CNN architectures; ResNet and AlexNet for the detection of rice plant disease. The data used to train the models include a combination of rice leaf images that were gathered locally from a rice field/farm in Ede, Osun State, Nigeria, and from an online repository. The dataset consists of 5200 images classified into four classes: Bacterial leaf blight, Brown spot, Blast, and Healthy, each containing 1300 images. The effectiveness of the two trained models was measured using classification performance metrics including Accuracy, Precision, Recall, and F1-Score. The finding from the study showed that The ResNet has a test accuracy of 95.25% as against 92.91% for the AlexNet. The ResNet had 0.93 precision, while AlexNet recorded a precision of 0.24. For recall, the ResNet model had 0.98 while the AlexNet model had 0.23 and for the f1-score, the ResNet model had 0.95 while the AlexNet model had 0.24. Generally, the ResNet model outperformed the AlexNet model in detecting rice plant diseases, most significantly, brown spot disease.

Key words: AlexNet, Convolutional Neural Networks, ResNet, Rice Plant Diseases.

1. INTRODUCTION

Rice (*Oryza sativa*) is a very important plant in agriculture, and it is the most extensively eaten staple food in many regions of the globe. Rice is consumed by about 75% of the global population, and it is a primary food for well over half of the population of the world (Sreevallabhadev, 2020). Although a variety of factors influence plant development, such as pests, soil characteristics, irrigation, topography, seed selection, humidity, nutrients, fertilizer, weather conditions, and biological factors, plant diseases account for more than 10% of overall plant output losses. Rice diseases have a severely damaging effect on the quantity and

quality of the output of rice production which can cause substantial losses in rice plant productivity (Chen et al, 2020). The identification of these diseases may be carried out in several ways, including manual and computer-vision-based approaches. The manual approach, which is based on human vision, involves the physical examination of the rice plants by plant pathologists. The computer-vision-based approach is an automated disease detection technique, which may involve an intelligent device being deployed in the plant field where video detectors are installed at multiple locations in the plant field or pictures of the rice plants are taken which 4frcdszwill be input into a system to see if the plant is infected (Upadhyay and Kumar, 2021).
Deep learning is a branch of machine learning in Artificial Intelligence (AI), which is primarily a neural network containing three or more layers. These neural networks try to replicate how the human brain functions (Sethy et al., 2018). As deep neural networks, various CNN models have been suggested by many researchers for the classification of rice diseases (Burhan et al., 2020), but limited work has been done in comparing these models to evaluate their performances. This study, therefore, proposes a comparative analysis of two CNNs in the detection of rice plant diseases, using a combination of data gathered on a rice farm site and an existing online repository data.

2. RELATED WORKS

In Mohanty, Hughes and Salathé (2016), a dataset that contained 54306 images, and plant diseases was identified employing two deep convolutional neural network architectures namely, AlexNet and GoogleNet. This dataset was collected from an online plant repository called Plant Village. In the study, sixty experimental setups were carried out using AlexNet and GoogleNet, the training approach adopted was training from scratch, and transfer learning, while the kind of images contained in the dataset were color, grayscale, and leaf segmented. The training-testing partitions were 80% - 20%, 60% - 40%, 50% - 50%, 40% - 60%, 20% - 80%, respectively. The accuracies obtained ranged from 85.53% to 99.34%. The lowest accuracy was 85.53% obtained from the experiment using AlexNet architecture, with the training from scratch approach implemented on the dataset containing gray-scaled images. This experiment was implemented on a train-set partition of 80-20%. The highest accuracy, 99.34% was achieved in the experiment using GoogleNet architecture. The training process was carried out using the approach of transfer learning on the PlantVillage dataset with a train-set partition of 80-20%. The findings showed that GoogleNet constantly outperformed AlexNet, while transfer learning consistently outperformed training from scratch. The colored form of the dataset gave the best results of the architectures.

In Rahman (2020), two recognized CNN architectures, InceptionV3 and VGG16 were tested in different environments for Identifying and recognizing rice diseases and pests employing convolutional neural networks. In a real-life scenario, 1426 images comprising eight different classes of rice diseases and pests were collected. The diseases considered were hispa, bacterial leaf blight, false smut, neck blast, sheath blight, brown plant hopper (BPH), and brown spot. The architectures were tested and further compared with another set of three popular CNN architectures that have memories that are highly efficient namely, SqueezeNet, MobileNetv2, and NasNet Mobile. Keras framework was used with TensorFlow as the backend for the training of the models. For all five architectures, fine-tweaking the pre-trained images collected from ImageNet yielded the best results. A new two-stage training model based on the concept of fine-tuning was established, allowing the suggested CNN architecture used in this study to perform effectively in a real-world setting. The best accuracy was attained by the fine-tuned VGG16 at 97.12%. In the absence of any previous training on the dataset from ImageNet, the Simple CNN architecture using two stages of training achieves similar accuracy (94.33%) and maximum precision. This model is instead taught from scratch.

The study in Krishnamoorthy and Parameswari (2021) applied transfer learning to train VGG-16, ResNet50, and InceptionV3 deep convolutional neural network models. The rice leaf picture dataset was acquired from The Kaggle API. The data comprises 5200 RGB color rice leaf photos in total, with each image containing just one disease. The dataset comprises images from three disease classes: brown spot, bacterial blight, and leaf blast, as well as images belonging to the healthy class. Each label class contains 1000 images in the training set, and each class has 300 images in the test set. The dataset was split in the ratio of 70:30 for training and testing purposes. The rice leaf pictures were used to test VGG-16, ResNet50, and InceptionV3 for classification. The suggested neural networks were implemented in Keras 2.4.3 using Tensorflow as the backend. By running 15 epochs, the VGG-16 architecture was altered using several hyperparameters, which achieved an accuracy of 87.08%. Using 10 epochs and twitching several hyperparameters, InceptionV3 and ResNet50 obtained their highest accuracies at 95.41% and 93.41% respectively.

In an experiment in Singh and Kumar (2021), three deep learning models, LeNet, VGG19, and MobileNetV2 were implemented to recognize rice plant infection. A dataset containing 2212 images of both diseased and healthy rice plants was used, among which 523 samples were utilized for the healthy category, and samples of 1689 images were used for the diseased category. The complete dataset was split into two sets, one set was used in training while the other was used for validation, at the ratio of 80:20. The training set contained 1768 samples, while the testing set contained 444 samples. 418 samples from the training set corresponded to the healthy image class, whereas 1350 samples were from the diseased class. In addition, there were 339 samples of diseased class images and 105 samples of healthy class images in the validation set. The major goal of using these multiple models concurrently was to highlight the working comparability between them. A confusion matrix was used as an evaluation metric to determine the accuracy of the experimentation. In contrast to MobileNetV2 and VGG19, it was discovered that LeNet performed better.

In a study by Natarajan et al. (2021), a transfer learning method with a deep convolutional neural network of the InceptionResNetV2 was demonstrated for the detection of diseases in rice leaves. The images of the rice leaves used in this experiment were obtained from an online repository, Kaggle. The data comprised 5200 images divided into three disease classes: leaf blast, bacterial blight, brown spot, as well as a healthy class. There was just one disease in each image. For each class label, the training set included 1000 images while the testing sets included 300 images. The dataset was partitioned into training sets and testing sets in 70:30 ratios. InceptionResNetV2 was implemented as the classifier. To increase the initial training image collection, the image augmentation approach was employed. Image modification techniques used for real-time augmentation include random resizing, rotation, splitting, and flipping images in vertical and horizontal directions. The library, ImageDataGenerator available by the Keras framework for deep learning was used to do this operation. Softmax activation was employed in the output layer to categorize the rice leaf disease class labels. Keras 2.4.3 framework with Tensorflow as the backend was used in implementing the deep neural network in the training and validation processes. Training the models using 15 epochs, the basic CNN model was modified using multiple hyperparameters and attained an accuracy of 84.75%. Using 10 epochs and modifying several hyperparameters, InceptionResNetV2 obtained an optimal accuracy of 95.67%.

3. METHOD

3.1 Dataset Description

The data used in this study consists of a combination of rice plant images that were collected from an online data repository and an onsite farm (rice farm site).

3.1.1 Online Data

Rice leaf images were obtained from Kaggle, an online repository for data science challenges. The dataset has a total of 5200 images, for four specific categories (1300 for each category); Brown Spot, Blast, and Bacterial Leaf Blight diseases, including a healthy class. The images contained a white background and only one leaf per image, this made it a ready-to-use dataset.

3.1.2 Onsite Data

Forty rice leaf images of the healthy class were locally collected from a rice field in Ede, Osun State, Nigeria, at latitude 07° 40′ North and longitude 04°30′ East, in April 2022, using a mobile camera Apple iPhone 6s (8 MP, f/2.2, 29mm). The initial size of the images was 2090 x 2787 pixels. To overcome the identification barrier, the assistance of a domain expert was solicited, who not only assisted in communicating with the farmer but also identified the healthy rice plants. Forty selected rice leaf images from the healthy-class data, which was obtained from the online data repository, were removed, and replaced with the forty rice leaf images obtained from the onsite farm. The dataset-splitting process used in this study is shown in Table 1. Image samples from the dataset for each classification are shown in Figure 1.

All images were resized to 255x255 pixels, irrespective of original dimensions, to account for any limitations imposed by camera specifications. As a result, the models that were trained thereafter would work with even low-quality images.

Table 1: Dataset Splitting

Class Name	**Total Number of Images**	**Number for Training**	**Number for Validation**	**Number for Test**
Bacterial Leaf Blight	1300	500	500	300
Brown Spot	1300	500	500	300
Blast	1300	500	500	300
Healthy	1300	500	500	300
Total	**5200**	**2000**	**200 0**	**1200**

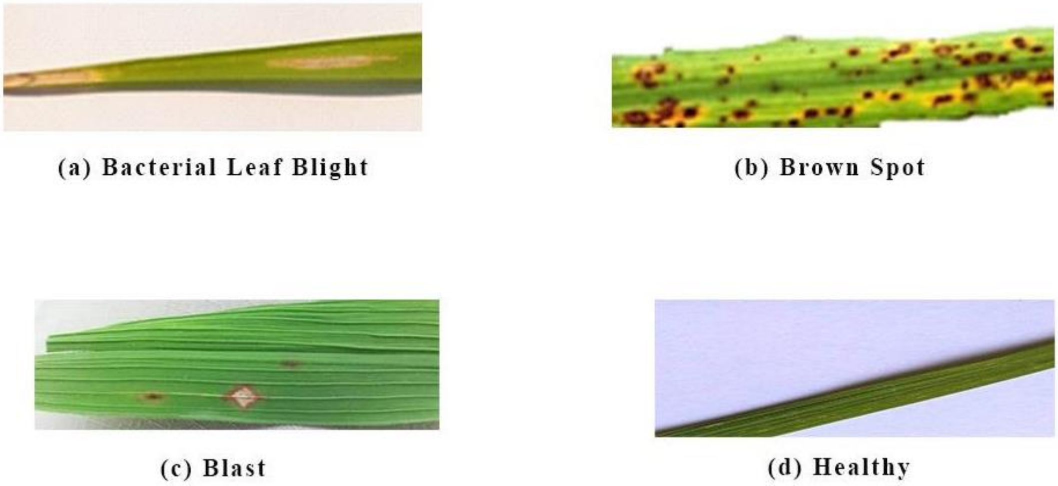

Figure 1: Sample Images of Rice Leaves per Classification

3.2 Workflow of the Rice Disease Detection Study

The workflow of the rice disease detection process consists of various phases for detecting and classifying the selected rice plant diseases. It starts with the acquisition of images to the various preprocessing stages down to the training phase, validation phase, testing phase, and finally to the classification and performance evaluation stages of the models. The block diagram and detailed architecture for this study are shown in Figures 2 and 3 respectively.

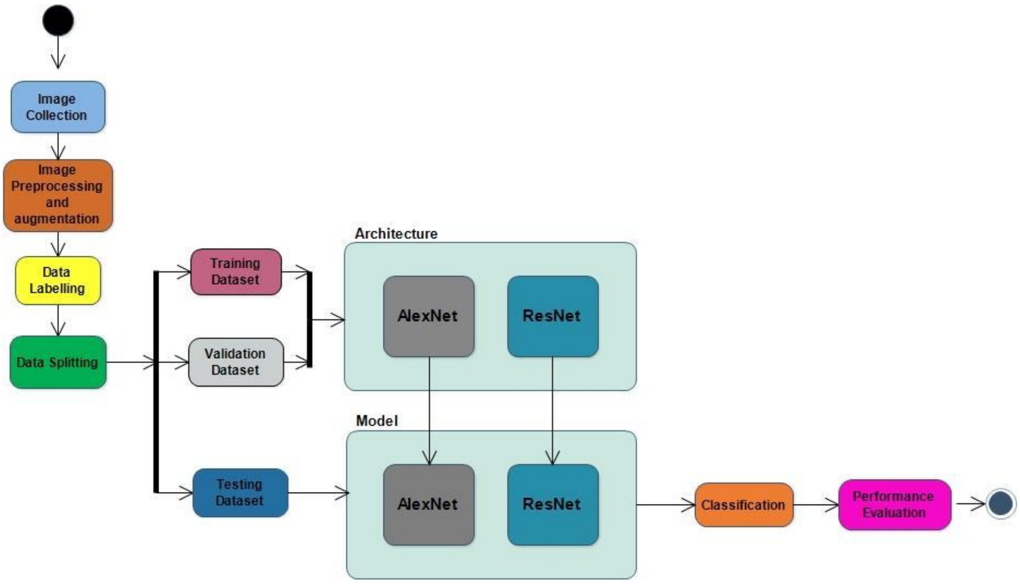

Figure 2: Block Diagram of the Study Workflow

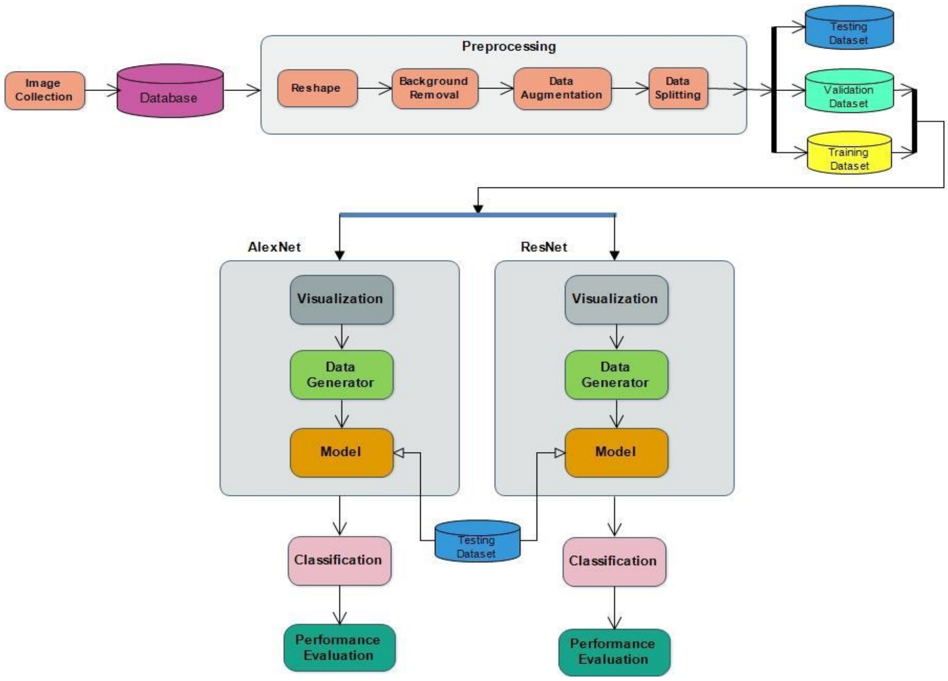

Figure 3: Detailed Architecture of the Study Workflow

3.3 The AlexNet and Resnet Architectures

The two CNN architecture considered in this study are AlexNet and Residual Network (ResNet). According to Alzubaidi et al., (2021), the AlexNet architecture is made up of eight layers. The model contains five convolutional layers with a combination of max pooling followed by three fully connected layers. The input size is most stated as 224x224x3, however, due to padding, it turns out to be 227x227x3. The first convolution layer consists of 96 filters with a dimension of 11x11 and a stride of 4. It then outputs a feature map of dimension 55x55x96 pixels. The next layer which is the first max-pooling layer has a dimension of 3X3 and stride 2. It outputs a feature map of dimension 27x27x96 pixels. This layer's activation function is ReLU In the second convolution layer, the 256 filters are reduced to a dimension of 5x5 each consisting of one stride and one padding. The output is 27x27x256 pixels. In the max-pooling layer, a dimension of 3x3 is used with stride 2. The resulting feature map gives a dimension of 13x13x256. The third convolution layer consists of 384 filters and has a dimension of 3x3, a stride of 1, and a padding of 1. It outputs a feature map of dimension 13x13x384 pixels. The fourth convolution layer consists of 384 filters with a dimension of 3x3, a stride together with padding is 1. Its outputs remain the same i.e., a dimension of 13x13x384. The final convolutional layer has the same features as the fourth. In the third max-pooling layer a dimension of 3x3 and stride 2 are applied, resulting in a feature map of dimension 6x6x256. In the first fully connected layer, the output size is 4096. followed by the second fully connected layer consisting of 4096 neurons. The final fully connected layer consists of 1000 neurons. ReLU is the activation function used in all levels, while Softmax is used in the output layer.

The Residual Network (ResNet) solves the problem of the vanishing/exploding gradient in AlexNet, by introducing the concept of Residual Blocks. In this network, the skip connections technique is used. The skip connection connects activations of a layer to further layers by skipping some layers in between. This forms a residual block. ResNets are made by stacking these residual blocks together. The approach behind this network is, instead of layers learning the underlying mapping, we allow the network to fit the residual mapping. The advantage of adding this type of skip connection is that if any layer hurt the performance of architecture, then it will be skipped by regularization. So, this results in training a very deep neural network without the problems caused by vanishing/exploding gradient. ResNet is the first architecture to outperform humans (Bezdan & Bačanin, 2019).

3.4 Implementation Platform

The model setup, data generation, training, validation, testing, and performance evaluation were implemented in Python. A Keras 2.4.3 framework with a Tensorflow backend was used to execute the proposed neural networks. Due to the system's constrained Graphics Processing Unit (GPU) capability, Google Colab was used for experimentation to make up for GPU resources. Each image was initially imported to Google Drive which was later mounted on Colab, due to memory size limitations.

3.5 Training and Validation Process

The training and validation datasets for each of the architectures contained 500 images each for the four classes. Both models were trained with the following parameters: Epochs = 50, Batch size = 128, Optimizer = Adam, Loss function = categorical cross-entropy.

4. RESULTS AND DISCUSSION

The dataset for each category of rice leaf (Blast, Bacterial Leaf Blight, Brown Spot, and Healthy) was split into three: 40% was used for training, 40% for validation, and 20% for testing. After the training and validation datasets had been used to develop a model for each of the CNN architectures, the test dataset was passed into the models to assess each model's performance. The metrics for evaluation used are accuracy, recall, precision, and F1-Score.
During the training time, the AlexNet model used 2 hours, 57 mins, and 1 sec to execute while the ResNet model used a lesser time of 2 hours, 15 mins, and 7 secs. The AlexNet model had a training accuracy of 92.60% and a loss of 0.26 over the total number of epochs. The ResNet model had a training accuracy of 95.94% and a loss of 0.11 over the total number of epochs. The accuracies for the training and validation process for each of the models, including their training time, are shown in Table 2.

Table 2: Summary of the Training and Validation Process

Model	Training		Validation		Training Time
	Accuracy (%)	Loss	Accuracy	Loss	
AlexNet	92.60	0.26	92.29	0.23	2h 57m 1s

ResNet	95.94	0.11	93.07	0.21	2h 15m 7s

The graphs for the cross-entropy loss and classification accuracy for AlexNet are shown in Figures 4 and 5 respectively. The curves for the cross-entropy loss and classification accuracy for ResNet are shown in Figures 6 and 7 respectively.

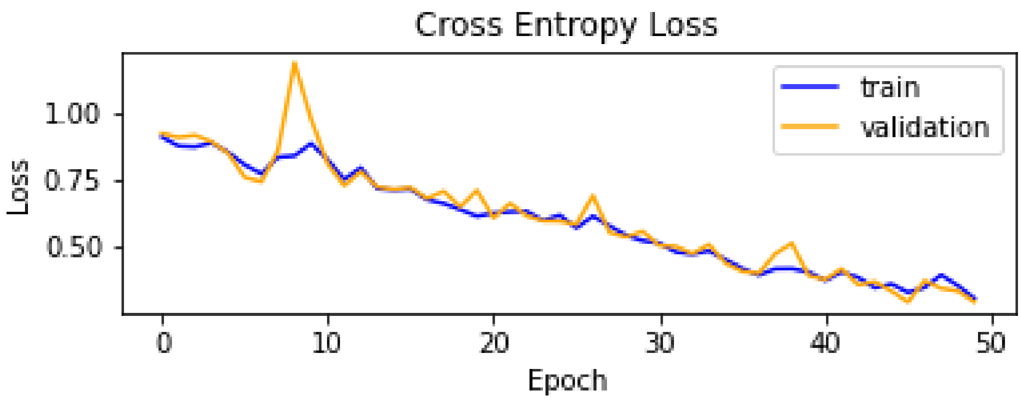

Figure 4: Training and Validation Loss Rate for AlexNet

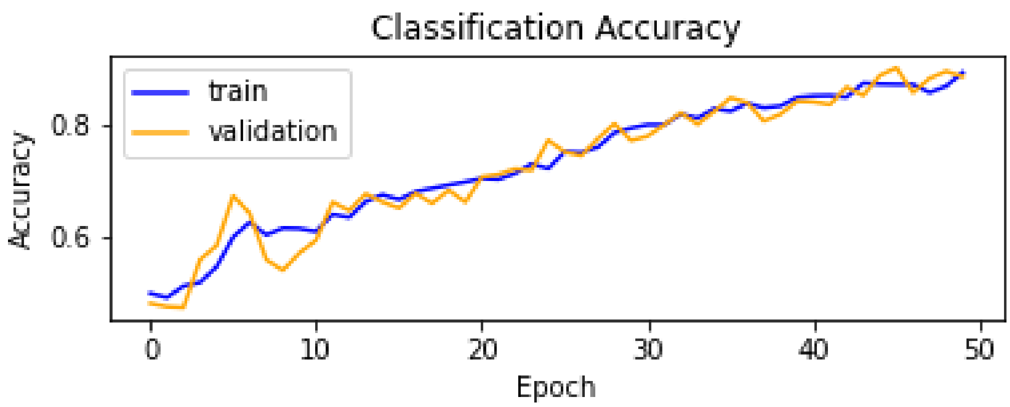

Figure 5: Training and Validation Accuracy for AlexNet

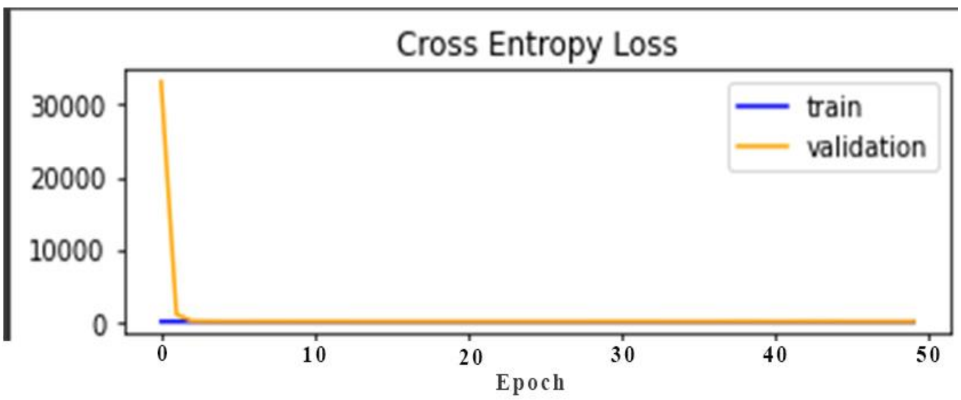

Figure 6: Training and Validation Loss Rate for ResNet

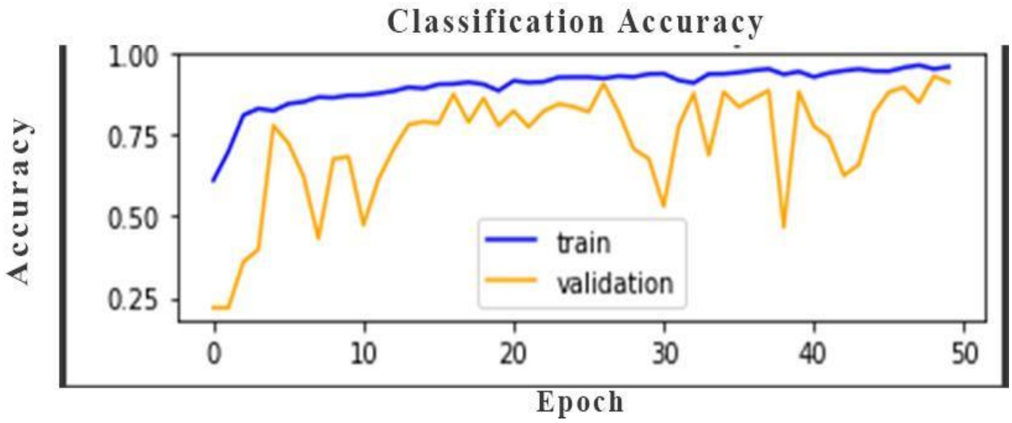

Figure 7: Training and Validation Accuracy for ResNet

4.1 Test Accuracies of the CNN Models

Table 3 shows the accuracy for each of the CNN architectures after predicting the classes with the testing dataset. The results showed that the ResNet architecture had a better result with an accuracy of 95.25%. The ResNet also had a lower cross entropy loss in the testing process which implies that the ResNet classification is more reliable than AlexNet.

Table 3: Test Accuracy of the Two CNN Models

Model	Accuracy (%)	Loss
AlexNet	92.91	0.28
ResNet	95.25	0.21

4.2 Confusion Matrix of the CNN Models

The confusion matrix compared the actual target value with those predicted by each of the CNN models for the classes considered. The class labels depicted in the confusion matrix are described thus: 0 - Bacterial Blight, 1- Leaf Blast, 2- Brown Spot, and 3- Healthy leaf Class. Figure 8 showed that the AlexNet architecture correctly classified the bacterial leaf blight category in 69 instances and wrongly classified the bacterial leaf blight in 231 instances; correctly classified the blast category in 68 instances and wrongly classified the blast disease in 232 instances; correctly classified the brown spot category in 64 instances and wrongly classified the brown spot in 236 instances; correctly classified the healthy rice plant in 63 instances and wrongly classified the healthy class in 237 instances.

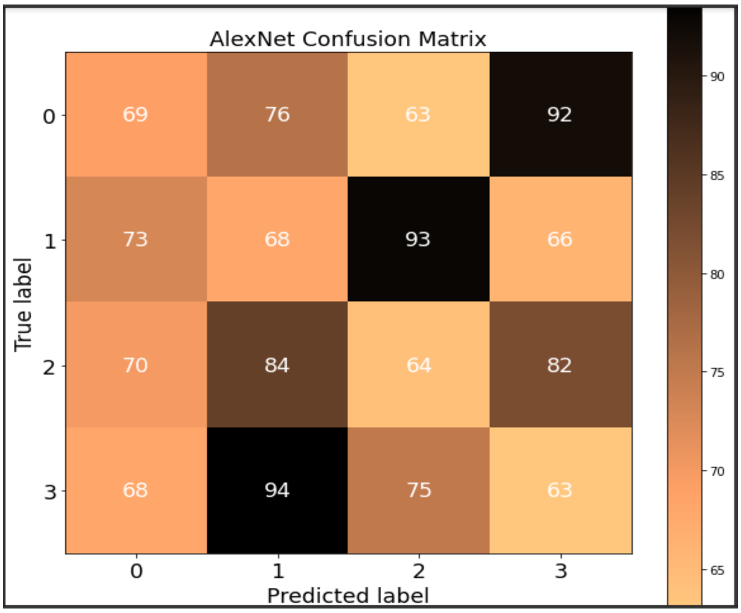

Figure 8: AlexNet Confusion Matrix

Figure 9 shows that the ResNet architecture correctly classified the bacterial leaf blight category in 292 instances and wrongly classified the bacterial leaf blight in 8 instances; correctly classified the blast category in 208 instances and wrongly classified the blast disease in 92 instances; correctly classified the brown spot category in 295 instances and wrongly classified the brown spot in 5 instances; correctly classified the healthy rice plant in all 300 instances and had no wrong classification instances.

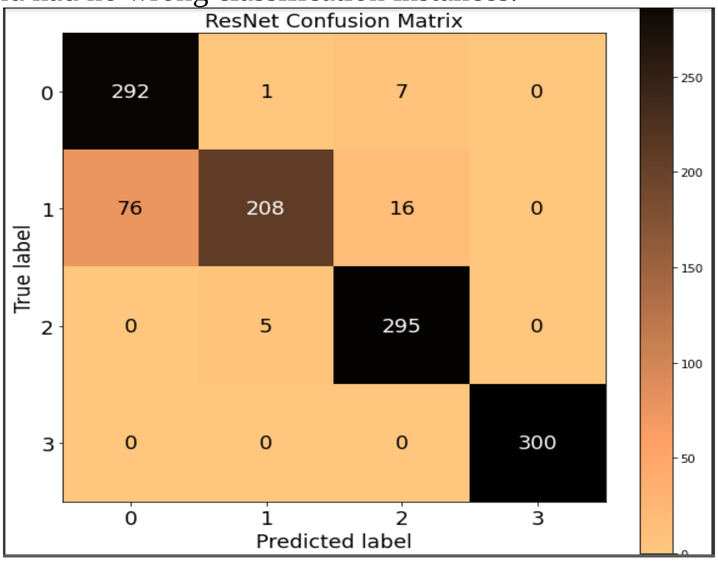

Figure 9: ResNet Confusion Matrix

4.3 Comparison of Performance Metrics of the CNN Models

The performance analysis of the results of the study showed that ResNet architecture performed better than **AlexNet**, with an average precision of 0.92, recall of 0.91, and f1-score of 0.91 for the disease categories considered. Details of the result are shown in Table 4.

Table 4: Precision, recall, and f1-score of the CNN Models

Class	Precision		Recall		F1-Score	
	AlexNet	ResNet	AlexNet	ResNet	AlexNet	ResNet
Bacterial Leaf Blight	0.23	**0.79**	0.21	**0.97**	0.22	**0.87**
Blast	0.27	**0.97**	0.29	**0.69**	0.28	**0.81**
Brown Spot	0.24	**0.93**	0.23	**0.98**	0.24	**0.95**
Healthy	0.27	**1.00**	0.27	**1.00**	0.27	**1.00**

Figure 10 compares the performances of AlexNet and ResNet models based on their accuracy, recall, precision, and f1-score values.

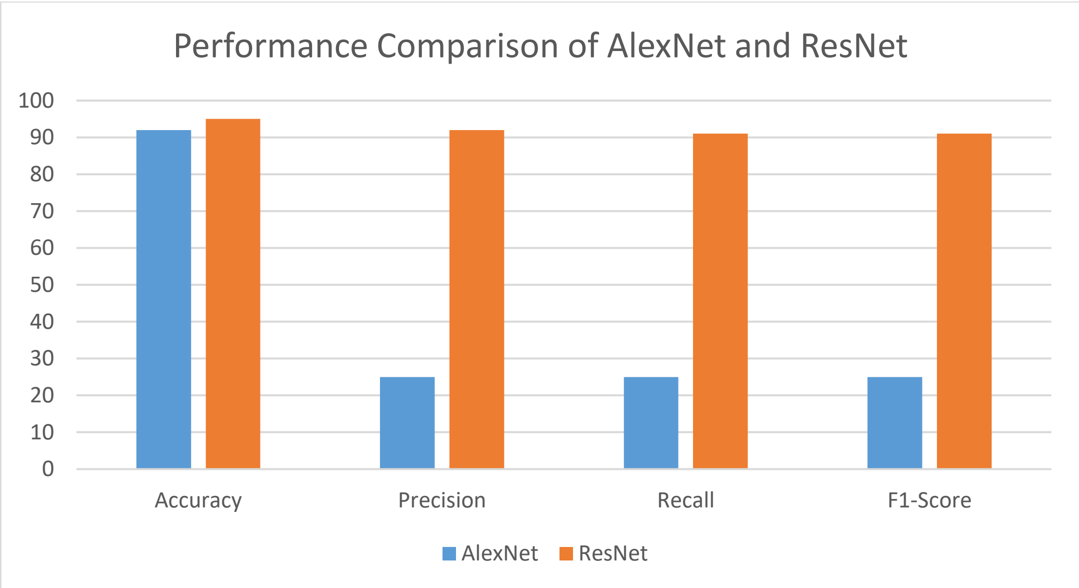

Figure 10: Overall Performance Comparison of the CNN Models

4.4 Discussion of Findings

The training accuracy of the AlexNet model, as shown in Table 2 was 92.60% while ResNet recorded an accuracy of 95.94%. Also, the validation accuracy for AlexNet was 92.29%, while that of ResNet was accuracy of 93.07%. The AlexNet model used more time to train as it was trained for 2h 57m 1s, while ResNet was trained for 2h 15m 7s. The cross-entropy loss values for the ResNet model during the training, validation, and testing processes were lower than the AlexNet model. This implies that the ResNet model had better classification reliability.

The AlexNet had an accuracy of 92.91% against 95.25% for ResNet (see table 4), implying that the ResNet outperformed the AlexNet in the testing process also. In Table 4, it was shown that in the classification of the bacterial leaf blight disease, ResNet, having a precision of 0.79, outperformed AlexNet, which had a precision of 0.23. Also, the ResNet model had a recall of 0.97 while AlexNet had 0.21. The f1-score of ResNet was also recorded to be 0.87 as against AlexNet having 0.22. Therefore, in the classification of bacterial leaf blight disease, ResNet outperformed AlexNet.

It can also be seen from Table 4, that in the classification of the blast disease, ResNet, had a precision of 0.97, while AlexNet had a precision of 0.27. Also, the ResNet model had a recall of 0.69 while AlexNet recorded a recall of 0.29. The f1-score of ResNet was also recorded to be 0.81 as against AlexNet having a recall of 0.2. Therefore, in the classification of the blast disease, ResNet also outperformed AlexNet.

Table 4 also showed that in classifying the brown spot disease, ResNet performed better than AlexNet. For precision, ResNet had 0.93 while AlexNet had 0.24. For recall, ResNet had 0.98 while AlexNet had 0.23 and for the f1-score, ResNet had 0.95 while AlexNet had 0.24. Also, in the general classification of the various rice diseases, ResNet outperformed AlexNet, specifically in the classification of the brown spot disease. In classifying the healthy class, ResNet recorded a maximum value of 1.00 while AlexNet recorded a value of 0.27 for f1-score, precision, and recall.

4.5 Performance Analysis of Findings with Existing Studies

The result from this study was compared with similar studies in the literature as shown in table 5.

Table 5: Summary Table of Related Works

S/N	Author(s) (Year)	Title	Dataset Source	Method Focus	Result (Test Accuracy)	Research Gap/Limitation
1	Mohanty et al. (2016)	Using deep learning for image-based plant disease detection	Online only	AlexNet	AlexNet-85.53%	No real-life image was used.
2	Rahman (2020)	Identification and recognition of rice diseases and pests using convolutional neural networks	Onsite only.	VGG16, InceptionV3, MobileNetv2, NasNet Mobile, SqueezeNet v1.1, Simple CNN	VGG16-89.19%, InceptionV3 - 91.17%, MobileNetv2- 78.84%, NasNet Mobile-79.98%, SqueezeNet v1.1-	There was a wide disparity in the number of images used for the various rice plant diseases.

					74.88%, Simple CNN-94.33%.	
3	Krishnamoorthy & Loga Parameswari (2021)	Rice Leaf Disease Detection Via Deep Neural Networks with Transfer Learning for Early Identification.	Online only.	ResNet-50, InceptionV3, VGG-16	VGG-16-87.08%, ResNet-50-93.41%, InceptionV3 - 95.41%.	The VGG16 architecture's training performance was incredibly slow.
4	Singh & Kumar (2021)	Rice Plant Infection Recognition using Deep Neural Network Systems	Not specified	LeNet, VGG19, MobileNetV2.	VGG19-77.09%, LeNet5-76.63%, and MobileNet-V2 - 76.92 %.	Image preprocessing techniques were not applied to the dataset before training.
5	Natarajan et al. (2021)	Rice leaf diseases prediction using deep neural networks with transfer learning	Online only	Simple CNN	Simple CNN-91.02%	The model validation process was not implemented in the study.
6	Proposed study	A Comparative Study of Two Convolutional Neural Network Models for	Online and onsite dataset	AlexNet, ResNet	AlexNet - 92.91%, ResNet - 95.25%	Only two CNN models were compared.

		the Detection of Rice Plant Diseases				

5. CONCLUSION

In this study, two Convolutional Neural Networks (CNN) namely, AlexNet and ResNet, were deployed to detect three different types of rice plant diseases (Bacterial leaf blight, Blast, and Brown spot) The data were collected from both online and onsite. A total of 5,200 images and a training-validation-testing partition of 40%-40%-20% were used to carry out this analysis. The datasets were trained and validated over 50 epochs. The ResNet and AlexNet models had a good level of cross-entropy loss which signified that there was an insignificant level of overfitting in both models. The performance metrics used to evaluate the models were Accuracy, Recall, Precision, and F1-score. The results showed that the ResNet outperformed the AlexNet model. ResNet had an accuracy of 95.25% while AlexNet had an accuracy of 92.91%. The ResNet model also gave a 1.00 score for the Recall, Precision, and F1 score in classifying the healthy class. As shown in this study, the ResNet CNN architecture invariably outperformed AlexNet in all the performance metrics that were evaluated and has proven to be a superior CNN model in the detection of rice plant disease when compared with the AlexNet model. In future work, some other rice plant diseases not included in this study would be added for consideration, and other CNN architectures would also be compared together with the ones considered in this study. The effectiveness and dependability of this study can be further increased by including additional critical parameters in the model's training, such as weather conditions, rice types, soil characteristics, moisture levels, etc. Also, incorporating the models into a web or mobile application would make it easy for farmers to upload pictures of their crops to identify diseased plants.

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