Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/190602

Aiding the Digital Eyes to Detect the Leaf-Spot Diseases in Rice Crops using DenseNet CNN Algorithms

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Received: 5 Feb. 2025, Revised: 26 Apr. 2025, Accepted: 21 Aug. 2025
Published online: 1 Nov. 2025

Abstract: To investigate the capability of deep learning models in identifying rice crop diseases. A convolutional neural network (CNN) based classification strategy was introduced in this re-search for high-resolution agricultural remote sensing pictures of paddy leaves. Various clas-sifications were tested and assessed based on specificity, accuracy, recall, precision, and F1-score. To analyse and comprehend the technique, a substantial quantity of samples obtained from open source panchromatic pictures with a resolution of 256x256 pixels were used for experimentation and verifying using MATLAB. This research relies on datasets that were acquired from the Kaggle repository. The dataset used for rice disease identification consists of 3,400 photos. These images are divided into 60 images for each of the seven different dis-ease categories such as Bacterial Blight, Downy mildew, brown spot, Dead Heart, Hispa, leaf blast, Tungro. There were a total of 550 photographs that were specifically chosen for valida-tion. The performance of DenseNet 201 under CNN was comparatively higher with the accuracy of 97% and precision of 99%.Later the study was extended towards the modified DenseNet, where in accuracy and elapsed time where improved eliminating the traditional three convolutional layers of DenseNet 201. The study also incorporated an extension to the modified DenseNet architecture, leading to improved accuracy and decreased elapsed time. An improvement was made by removing the traditional three convolutional layers found in DenseNet 201.

Keywords: CNN algorithm, DenseNet-201, AlexNet, GoogleNet, ResNet-50, NasNet Mobile, ResNet-101, Xception, Sustainable agriculture, Crop monitoring

1 Introduction

Paddy leaves are often the first to display symptoms of various microbial diseases. Although some research studies have been dedicated to identifying rice disease using CNN [1,2,3,4],there are still deficiencies in the existing study on CNN-based rice leaf disease detection. Initially, it is necessary to undertake a detailed research on the prevalent epidemic illnesses specific to a particular nation, since rice diseases vary across various countries. Instead of relying on a limited number of key classes, it is advisable to expand the range of rice illnesses. In addition, a study should be conducted to examine if paddy leaf illnesses may be detected with greater precision using original CNN architectures, transfer learning, or ensemble approaches [5,6,7,8]. This study aims to evaluate effectiveness of advanced CNN architectures, including DenseNet-201, GoogleNet, AlexNet, ResNet-50, Nasnet Mobile, ResNet-101, and Xception in accurately classifying rice plant diseases.

The fundamental purpose of this research is to develop a model that is capable of producing the highest possible degree of accuracy in the categorisation of rice

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leaf diseases. Support Vector Machines (SVM) may be used for the identification of paddy leaf diseases using manually derived features, demonstrating efficacy on smaller datasets; however, it may encounter difficulties with complicated, high-dimensional data and extensive datasets. Conversely, CNN is superior for detecting paddy leaf disease since it autonomously extracts features from raw pictures, manages extensive and intricate datasets, and often provides more accuracy, although necessitating increased computer resources and prolonged training durations. Using convolutional neural network (CNN) algorithms may identify diseases in paddy leaves with a high degree of accuracy reaching up to 98% in optimised configurations. Because of this precision, diseases may be reliably and promptly identified, allowing farmers to manage the illness fast and effectively and intervene before it becomes extensively disseminated. The accuracy is conditional on the data quality, the convolutional neural network (CNN) model used, and the model's capacity to generalise to other scenarios.

This study presents a thorough examination of many research that are focused on developing customised CNN-based methods and transfer learning. A range of hyperparameter configurations, techniques for fine-tuning models, and performance measures like accuracy, precision, recall, and F1-score used in different research are discussed. It aims to evaluate the effectiveness of advanced CNN architectures, including DenseNet-201, GoogleNet, AlexNet, ResNet-50, Nasnet Mobile, ResNet-101, and Xception in accurately classifying rice plant diseases. Computational training of neural networks is arduous and time-consuming, sometimes spanning from days to weeks. This constrains the deployment of Convolutional Neural Network (CNN) in real-time research domains where computing efficiency is paramount. Hence, it is necessary to determine suitable and improved processing speed in order to fulfil the demands of these real-time applications. A modified DenseNet architecture was extended in this study, for improving computing performance to fulfil the demands of real-time applications [9,10,11,12].

By synthesising previous research on rice plant disease diagnosis and management, the authors of this study hoped to improve upon existing disease detection models. They set out to find preexisting concepts and technologies that excelled in this domain. The results have been summarised in Table 1.

2 Related Works

From Table 1, it is shown that convolutional neural network-based rice disease diagnosis still faces problems in practice, including inaccuracy, data size, and processing requirements, despite the positive results. Computationally intensive training and training of convolutional neural networks for disease detection in rice may be time-consuming and resource-intensive. In order to find widespread use, convolutional neural network based rice illness identification must resolve this issue. The present study on rice disease detection using convolutional neural networks primarily emphasises enhancing accuracy. A remarkable degree of recognition accuracy has been attained by optimising the network topology and preparing the data. It is crucial to improve the detection rate of convolutional neural networks to make them more useful for rice disease diagnosis. There have been several advanced ML approaches discovered for the detection of rice plant diseases, including ResNet, DenseNet, MobileNet.

3 Methodology

The study primarily aims to detect rice leaf illnesses by experimental analysis, using pre-trained models of Convolutional Neural Networks like DenseNet-201, GoogleNet, AlexNet, ResNet-50, Nasnet Mobile,ResNet-101, and Xception. The technique was devised via deep learning algorithms applied to a large dataset of 3400 photos representing six distinct categories of rice diseases: Bacterial Blight, Downy mildew,brown spot, Dead Heart, Hispa, leaf blast,Tungro. The evident efficacy of convolutional neural networks (CNNs) has transformed the field of rice disease detection and localization using leaf analysis. Recent research conducted by CNN indicates a growth in the use of CNN for the detection and segmentation of rice leaf diseases [23,24,25].

Therefore, a sick rice leaf that exhibits distinct variations in colour, texture, and size compared to a healthy leaf presents an opportunity to use a Convolutional Neural Network (CNN) for image analysis. This allows for the collection of information on pixel inconsistencies over the whole leaf [26,27,28]. Every pixel in a leaf is anticipated to exhibit similarity in terms of any attribute or quality that is observable, such as colour, intensity, or texture. However, when there is a tiny cluster of pixels that deviates from the rest, it indicates an inconsistency within an item or the existence of additional objects.After analysing the trial findings, the most optimal CNN model for enhancement has been determined. The intended strategy is to enhance the efficiency, and simplicity of the model.

After doing a comprehensive analysis of the model and its architecture using particular pretrained models, necessary modifications are made to the network in order to rectify any discovered shortcomings. Dataset is executed using the modified network setup to evaluate its performance.

The Kaggle library was scoured for the sets of data used in this investigation. The rice illnesses and deficient disorders submitted photographs were scaled and enhanced. The contaminated regions of the photos were identified using ground truth masks. A dataset was created by extracting annotations and masks from photos

Table 1: Comparative Analysis of prior research

Reference	Rice diseases	Data set	Models	Accuracy	Remarks
[13]	Neck Blast, False Smut, Rice Leaf Blast, Brown Spot Sheath Blight	Rice disease dataset	DenseNet -121 model, SE-ResNet-50 model, ResNet-50 model	91%	Generalises well enough for rice disease detection. Rice diseases may be identified quickly, cheaply, and accurately using this software.
[12]	Brown Spot	UCI machine learning disease data set	VGG19 and CNN	93%	The training accuracy achieved was 93%, demonstrating the success of this study in detecting recognising diseases in leaf images.
[14]	Brown spot, Sheath, blight, Blast, Leaf streak	Sony camera and a mobile phone were used to acquire a total of 1500 images.	CNN	85%	Increasing the number of datasets used to train the model might potentially improve its accuracy, which has been impeded by the absence of datasets.
[15]	leaf blast, brown spot, and bacterial blight and healthy	5200 images from kaggle website	InceptionResNetV2	87%	The efficacy of the given model may be further improved by using large datasets of rice disease pictures.
[16]	Brown spot, Rice hispa, Leaf blast	Public rice disease dataset	ADSNN-BO model, Mobile Net model	94.65%	The training accuracy rate of 94% is substantially greater than prior research. For improvement, this ADSNN-OB model needs optimisation methods
[17]	leaf blast, leaf folder, and brown spot	1634 rice plant photos from the rice field	YOLOv8	89.90%	Poor accuracy. Pre-processing images before training the model may enhance it.
[18]	Leaf blast, Sheath rot, false smut, bacterial leaf blight, brown spot	Kaggle data set	CNN	88.93%	Performance and process of the suggested model are ineffective.
[19]	Bacterial leaf blight, brown spot, black spot, leaf blast, and leaf blight	openly accessible rice leaf disease photos for disease categories and one healthy category from kaggle	Deep Spectral Generative, Adversarial Neural Network	97%	The training accuracy rate of 97% is much higher than the accuracy rates seen in previous studies published in the literature
[20]	False Smut, Brown Plant Hopper, Bacterial Leaf Blight , Neck Blast, Stemborer ,Hispa ,Sheath Blight , Brown Spot	1426 pictures of rice pests and illnesses taken from BRRI's paddy fields)	Two-stage small CNN architecture	93.30%	Less-featured stage two model learning performance. After two training cycles, simple CNN is accurate and precise.
[21]	Brown Spot, Hispa, Leaf, Blast, Bacterial Leaf, Leaf Smut	Datasets of 120 and 2092 samples, respectively, combined	VGG19, LeNet5, MobileNet- V2	Mobile Net and VGG19 have equal accuracy.	A low level of accuracy is seen here. Image preprocessing methods used before training the model could make it better.
[22]	Bacterial Leaf Blight, Brown Spot, and Leaf Blight	240 images from paddy fields	multi-class SVM	86.51%	A lack of precision.

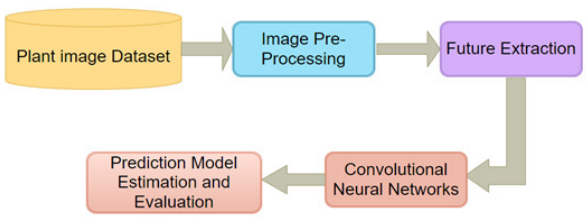

Fig. 1: Flow Diagram Convolutional Neural Netwoks

of rice leaves at a ratio of 70:30. This freshly generated dataset was then subjected to DL segmentation designs. Following are the metrics that were used to assess the segmentation method: recall, accuracy, precision, dice loss, and dice coefficient.The dataset utilised for disease detection in rice contains three thousand four hundred images collected for testing breaking them down into 60 images each category of nine distinct diseases: Bacterial Blight, Downy mildew, brown spot, Dead Heart, Hispa, leaf blast ,Tungro. A total of 550 photos were also designated for validation.To analyse and train the various models for illness identification, we referred to secondary data. One group of photos is used for training, another for validation, and a third for testing. The training set contains 75% of the total images, the validation set 10%, and the testing set 15%. The photographs are in .jpg format and have a size of 128×128 pixels [29,30,31].

All of the images were taken on a uniform white background and under the same lighting conditions. Figure 1 shows the working flow diagram of CNN. The next step is to extract the area containing the sick spot using picture segmentation. The primary challenges in using CNN models for disease detection in rice leaves are the need for large annotated datasets, substantial computing resources for training, and the potential for over fitting, particularly with restricted or unbalanced data. Furthermore, discrepancies in leaf pictures caused by illumination, angles, and background interference might diminish the model's precision. These challenges can be mitigated through techniques such as transfer learning to utilise pre-trained models, implementing regularisation techniques such as dropout to avert over fitting, tackling class imbalance through methods like class weighting, and applying pre-processing techniques to reduce the effects of lighting, angle, and background variations on leaf images.

In this study k-means clustering method to categorise all of the objects in the collection. Us-ing K-means clustering, similar leaf pictures or qualities (such colour, texture, or shape) may be grouped into distinct clusters. This can help in paddy leaf disease diagnosis by making it easier to identify different disease patterns or distinguish between healthy and ill leaves. By grouping pixels with similar patterns, this method makes it easier to segment leaves or identi-fy disease signs, which in turn allows for further analysis or classification.Initially, a photograph of an easily recognisable diseased rice leaf is chosen from the collection. It is essential to enhance the resolution of the image in order to provide a high-contrast representation when exposed to natural lighting conditions, subsequently converting it into a greyscale image [32,33,34]. After that, in order to examine the picture segmentation, the RGB to HSV colour format is used. Those hues, saturation levels, and values were extracted using HSV colour models. Further investigation makes use of the colour space transformation's hue component.

This study aimed to examine the performances of seven network models in order to determine the most op-timal models. Transfer learning in paddy leaf disease identification use pre-trained models to exploit learnt characteristics from extensive datasets, facilitating expedited training, enhanced accuracy with little data, and superior generalisation for disease diagnosis in paddy leaves with a reduced number of labelled pictures.These models have developed strong feature extraction skills that can be tailored to agricultural datasets. It may be optimised for the classification of rice illnesses. Such models are specifically developed to filter unprocessed photos via numerous layers and finally categorise them into certain groups.

The illness prediction results for each network model were divided into four categories: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) [35]. False positive findings indicated the presence of illnesses other than the one being tested for, whereas genuine positive results accurately predicted the specific ailment. The performance metrics of accuracy, precision, recall, specificity, and F1-score were derived from these observations. The implementation of this rigorous assessment approach allows a thorough understanding of the efficacy and suitability of each deep convolutional neural network (CNN) model within the particular domain of rice disease classification. This process sets the stage for detailed debates and meaningful conclusions. This section presents a thorough statistical study that focuses on evaluating machine learning-based methods for classifying rice leaf diseases using deep features [36].

4 Results and Discussion

Multiple learning models were trained and validated using GPUs that were available on the Google Colab platform. Initially, investigations were carried out using data on several CNN models including ResNet-50, ResNet-101, AlexNet, GoogleNet, NasNet Mobile, DenseNet-201, and Xception. Initially, the models' categorization performance is provided. Subsequently, the comprehensive metrics for those models are deliberated. The models underwent a thorough evaluation, taking into account important parameters such as accuracy, F1 score, Precision, Recall, and Specificity [37].

The DenseNet-201 model exhibited exceptional performance in classification with the use of transfer learning, as witnessed. Because of its deep design and excellent feature reuse, DenseNet-201 achieves better results for paddy leaf disease classification than other networks. Therefore, in this portion, specific focus was given to the profound characteristics derived by

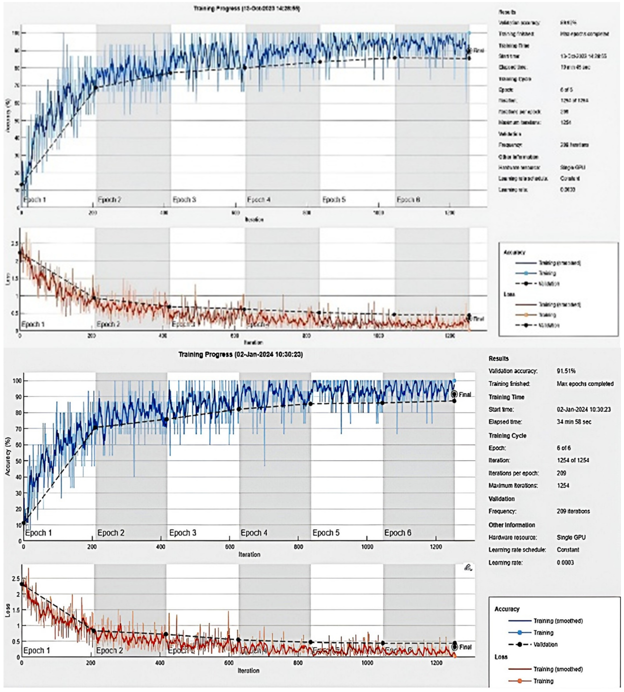

Fig. 2: Network Training progress Graphs for varoius CNN Algorithm

DenseNet-201 for more comprehensive examination. In order to train the machine learning model for classification, we first extracted the deep features from DenseNet fully connected layer. The findings presented the test accuracy and time required to complete prediction achieved by modifying the design of DenseNets. The DenseNet model may be used to identify illnesses in several crops, not only rice.Due to its ability to extract detailed information from images, it can identify pests, diseases, and nutritional deficiencies in many crops.

To ensure accuracy, the model must be fine-tuned and trained using crop-specific datasets.This assessment is a thorough evaluation that provides important information on the effectiveness and appropriateness of using machine learning methods together with deep features to accurately classify rice leaf diseases [38]. These results have important implications for the creation of strong and dependable diagnostic tools in the area of plant pathology. Figure 2 represents network training progress graphs for various CNN algorithms.

The progress graphs for various CNN alogorithm indicate that as the number of iterations for each epoch grows, the training accuracy generally improves gradually or sometimes decreases, while the loss consistently decreases [39]. A confusion matrix is a graphical tool that offers a concise depiction of the degree to which a model is providing inaccurate classifications across different categories. The confusion matrix may be used to visually represent the performance of the five submodels.The rows

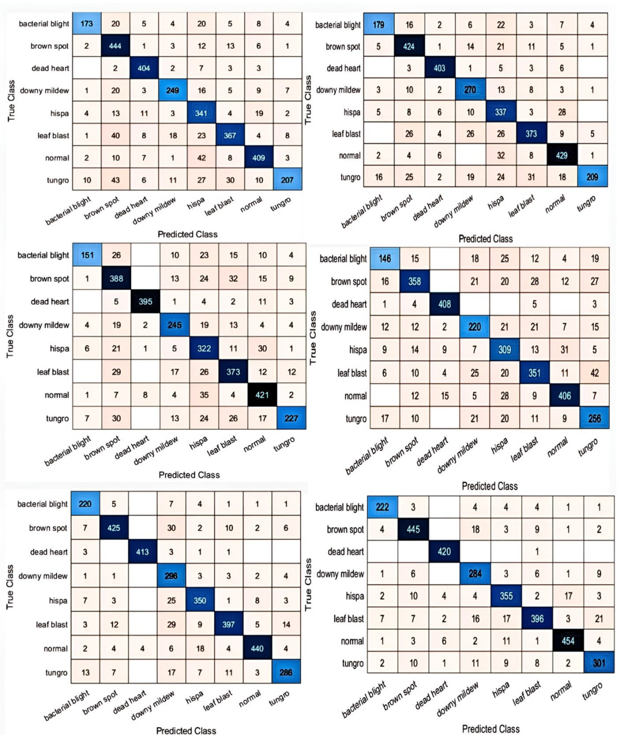

Fig. 3: Confusion Matrix for Various Algorithms

of confusion matrices represent the true categories of diseases, whereas the columns represent the expected categories of diseases [39]. The values located along the diagonal of the matrix represent the precise identification performed by the model within the classifications of true positives (TP) and true negatives (TN). Inaccurate identification of false positives (FP) and false negatives (FN) is represented by the off-diagonal values, where lesser numbers indicate a lower frequency of misidentifications [40].

The diagonal values exhibited significant magnitudes, whereas the remaining values were comparatively minor, indicating the high efficacy of all submodels in accurately identifying many forms of rice disorders [41]. The magnitude of the hue is directly proportional to the proportion between the numerical value at a specific location and the total numerical value inside the row. Consequently, the colour on the diagonal symbolises the rate of illness recall. Based on the confusion matrix, the DenseNet-201 submodel had superior performance compared to the other submodels in accurately classifying various illnesses, particularly in identifying leaf blast, false smut, and sheath blight rice diseases. The confusion matrices of the split test set of pictures for the six distinct kinds of disease of rice are shown in Figure 3.

Table 2 presents comparitive analysis of outcomes obtained from the CNN networks using transfer learning. The testing and findings reported here have significant importance in the construction of models using limited datasets [42]. Typically, a model is considered better when it has high Precision, high Recall, and high Specificity. The efficacy of the suggested architecture was evaluated by comparing it with transfer learning and eight individual CNN de-signs. Experimental investigations were carried out on both the original and enhanced versions of the picture dataset. The testing results suggest that the xception model demonstrated a comparatively low level of precision, recall, F1-score, and specificity in detecting leaf illnesses, culminating in an accuracy rate of 94.50% . Nevertheless, with the implementation of transfer learning, the DenseNet-201 and ResNet model achieved an accuracy of 98%.After evaluating the average accuracy, Precision, Recall, F1-score, and Specificity of CNN net-works using transfer learning on the enhanced datasets, it was determined that the modified DenseNet-201 model outperformed existing CNN designs [43].

Table 2: A comparative analysis of the performance of several deep learning models

Classification Methods	Accuracy (%)	Precision	Recall	F1-score	Specificity
ResNet 50	95.05	0.6318	0.8882	0.7384	0.9704
GoogleNet	95.87	0.749	0.8524	0.7973	0.9796
AlexNet	95.63	0.7239	0.8964	0.801	0.9777
DenseNet - 201	97.65	0.9289	0.9289	0.9289	0.9942
Nasnet Mobile	95.01	0.6318	0.8882	0.7384	0.9704
ResNet 101	96.37	0.9267	0.8996	0.913	0.9942
Xception	94.5	0.6084	0.7053	0.6532	0.968

To enhance performance, overcome limitations, or cater to specific applications, making them even more powerful for image recognition, some modifications are carried out in our proposed method. Modified DenseNets are convolutional neural network (CNN) architectures that make alterations to the original DenseNet architecture in order to achieve specific objectives [44]. Altering the architecture of DenseNet-201 entails the addition or removal of layers while preserving the dense connection framework. DenseNet-201 consists of dense blocks and transition layers; hence, any alterations must adhere to this framework to maintain the model's efficacy [45]. By making modifications to DenseNets, it is possible to enhance their performance by addressing certain restrictions. This may ultimately lead to increased accuracy when it comes to image recognition tasks. These modifications may resolve problems like over fitting in deeper networks and accommodate resource constraints by developing more efficient versions of DenseNet. Improvements in feature extraction and model generalisation led to breakthroughs in paddy leaf disease diagnosis via modifications of DenseNet-201 layers. Moreover, the ability to customise the DenseNet structure empowers researchers and developers to adapt the network to particular use cases or limitations in hardware, hence amplifying its adaptability and efficacy in many situations [46]. Figure 4 depicts a modified DenseNet architecture where three of the convolutional layers have been eliminated.

697	conv5_block32_0_bn Batch normalization with 1888 channels	Batch Normalization	7(S) × 7(S) × 1888(C) × 1(B)	Offs... 1 × 1 × 18... Scale 1 × 1 × 18...	TrainedM... 1 × 1 ... TrainedV... 1 × 1 ...
698	conv5_block32_0_relu ReLU	ReLU	7(S) × 7(S) × 1888(C) × 1(B)	-	-
699	conv5_block32_1_conv 128 1×1×1888 convolutions with stride [...	2-D Convolution	7(S) × 7(S) × 128(C) × 1(B)	Wei... 1 × 1 × 188... Bias 1 × 1 × 128	-
700	conv5_block32_1_bn Batch normalization with 128 channels	Batch Normalization	7(S) × 7(S) × 128(C) × 1(B)	Offset 1 × 1 × 128 Scale 1 × 1 × 128	TrainedM... 1 × 1 ... TrainedV... 1 × 1 ...
701	conv5_block32_1_relu ReLU	ReLU	7(S) × 7(S) × 128(C) × 1(B)	-	-
702	conv5_block32_2_conv 32 3×3×128 convolutions with stride [1 1...	2-D Convolution	7(S) × 7(S) × 32(C) × 1(B)	Weig... 3 × 3 × 128... Bias 1 × 1 × 32	-
703	conv5_block32_concat	Depth concatenation	7(S) × 7(S) × 1920(C) × 1(B)	-	-

Fig. 4: Modified DenseNet Architecture

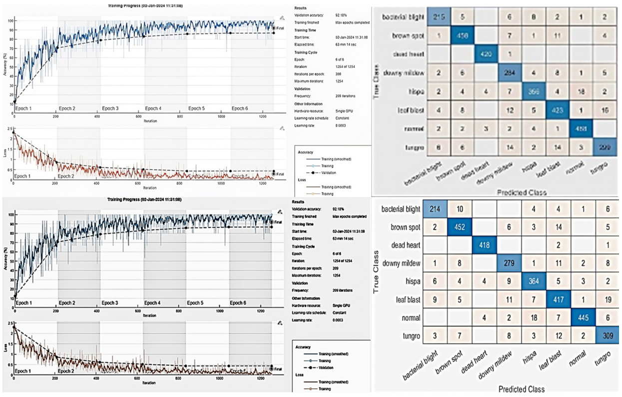

Fig. 5: Training Graph and confusion Matrix for DenseNet and Modified DenseNet Model

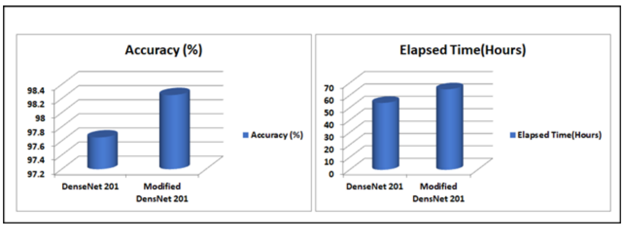

Fig. 6: Performance comparision of DesNet and Modified DenseNet Model

Figure 5 depicts training graphs and confusion matrix for DenseNe-201 and modified DenseNet 201 model. Figure 6 reveals performance comparison of DenseNet-201 and modified DenseNet-201models. From the findings the computational complexity have optimized in our proposed model and fine-tuned for our specific dataset. This has resulted in an improvement in accuracy and a reduction in the elapsed time for our modified dense Net model.

5 Conclusion

When it comes to solving prediction problems using input visual data, convolutional neural networks (CNNs) are generally considered to be the optimal choice. Its paramount importance cannot be disregarded due to its little need for pre-processing. The present research explores the use of cutting-edge neural network-based computer vision techniques for the purpose of detecting rice leaf fungal diseases. A comprehensive examination of many modern and conventional convolutional neural network structures had shown their remarkable efficacy in addressing the challenge. The finding of our proposed system shows that DenseNet-201 surpassed the competition in all evaluated metrics, regardless of the circumstances. Upon exhaustive comparison with all prior research on the matter, the enhanced DenseNet model demonstrated the highest accuracy rates of 98% for blast illnesses, therefore establishing its superiority in the identification and diagnosis of a wide range of disorders that impact rice plants. By around 6%, our suggested approach surpasses the current state-of-the-art. Given its exceptional performance and real-time capabilities, our suggested system has the potential to revolutionise the detection of leaf diseases and enhance AI-based diagnostic tools in agriculture. The primary contention of our study is that the challenge of automating the identification of rice fungal infections may be overcome by using meticulous data collection and annotation procedures conducted beforehand. Indeed, underfitting does arise because to a constraint in the design update of DenseNet-201.Utilising thermal, multispectral, and hyper spectral imaging enhances the precision of plant disease detection. Subsequent research should prioritise the development of models capable of effectively analysing pictures obtained under challenging lighting conditions, adverse weather conditions, and other severe scenarios. To enhance disease management, it is essential to simultaneously study several illnesses, irrespective of their specific regions of effect on the plants. Furthermore, the development of user-friendly apps is essential for facilitating the seamless incorporation of technology.

Acknowledgement

This research is partially funded by Zarqa University

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