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Analytical Study of Models for Rice Leaf Disease Detection Using AI and Deep Learning

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ABSTRACT

Rice is one of the most significant crops across the world, especially in Asian countries, where it majorly contributes to the national economy. With the constant change of human activities, the quality of the atmosphere, land and water bodies has also changed this led to an increase in plant diseases. The production of rice is seriously affected by various leaf diseases such as bacterial blight, brown spot, and leaf smut. As these diseases are numerous, they are difficult to identify by traditional manual techniques, which are more time-consuming and led to human errors. It is crucial to detect these diseases early and accurately in order to minimize losses in yield and make cultivation sustainable.

Deep learning models are used in this research to determine the best paradigm to use in automatic rice leaf disease detection. Convolutional neural network (CNN) models such as DenseNet121 (Densely Connected) are evaluated on a publicly available leaf images dataset. CNN has proven to be most significant and functional in image processing due to its potential to extract the components of an image. In this work, we inspect different models of CNN, especially targeting on Desnet121 architecture. Dense Net initiate dense connectivity between different layers. Layer 1 sends output to the layer 2,3,4. Layer 2 sends output to the 3,4,5…so on. Each layer receives information from the previous layer. The models are taken away on the basis of accuracy, precision, recall, F1-score, and computational efficiency. Experimental results demonstrate classification results much better than using a standard Convolutional Neural Network (CNN) trained from scratch. As well, it emphasizes on the potential of CNNs with optimization and synthetic data generation techniques to further improve and enhance model accuracy. In general, this study suggests that CNN models like Dense Net can provide a speedy and dependable way to detect rice leaf diseases and help farmers and experts to detect these diseases initially and reduce batch loss. The discovery of this research emphasizes on the deep-learning models for real-time and rice disease detection, offering profound observations for future agriculture systems in developing countries.

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Introduction:

Agriculture is the backbone of the world's food and nutrient security [1]. Among all, rice holds the centre of attention mainly in countries like Pakistan, China, Bangladesh, India and many more due to its economic and nutritional values [2, 3]. It nourishes more than half of humanity and plays a key role in the economic development of these countries. But the accelerating plant diseases due to different changes, such as environmental changes, climate shift, and inefficient agriculture, have become dangerous for reliable rice production. Most of these diseases originate from the leaves of the plant, from which the farmer can detect them early visually. After detecting the symptom, it is important to make crucial decisions to protect the whole field because some diseases spread rapidly and damage the whole crop.

In past, AI and deep learning have helped a lot to the agriculturist by creating new opportunities by converting traditional agricultural techniques with modern ones [4, 5]. One of the most successful ways to detect plant disease is image-based plant disease recognition, which is the application of AI [6]. A method convolutional neural network (CNN) is known for its ability to pull out fine-grained patterns from the images and perform old techniques to get output [7, 8]. This study mainly focuses on the DenseNet121 architecture of the CNN for rapid and correct spotting of leaf diseases in rice plants, particularly brown spot, leaf stunt and healthy leaves. DenseNet121 is magnificent because of its interconnectivity density, in which every layer gets characteristic maps from the preceding layers, maximum utilization of the previous layers, improving gradient flow. It helps the model to be more accurate and precise [9, 10].

Rice fields continuously struggle with the fast spread of bacterial, fungal, and viral diseases, and they affect plants in different ways, such as it damage its texture, structure and colour. Changes in the atmosphere also support some diseases like brown spot, leaf stunt and many others to grow rapidly. People living in farming areas usually use traditional techniques and limited trained methods for the detection of these diseases, that result in lower production [11].

Recent studies use different image processing and deep learning methods to detect these diseases. These methods use old models like Support Vector Machine (SVM), Random-Forest (RF) and many more [12]. These procedures use traditional manual features like colour characteristics, texture detail and histograms. These methods work with some limitations, such as detecting disease through human visuals; in this process human eye cannot detect the small and complex details of the disease on the leaves. It might be due to the cluttered scene; different light effect and these models cannot identify the stages of the disease, whether it is too early or too late to find out [4]. At the same time, deep learning models, mainly CNN, have greater accuracy than these old methods. Studies show that CNN architectures that are deeper are better for these diseases. In an agricultural field DenseNet121 method is executed in a better way because of it recondition feature and consistent workflow. After all these enhancements, there are still some problems that need more attention. To increase rice production and reduce the losses, smart agriculture is used for rice leaf disease detection. With the help of images, detecting plant disease is very significant because leaves represent early indications, and these are easily recorded by the cameras through which the images are taken. When these images are captured, they show

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properties that resembles with different disease symptoms, this result in difficulty in identifying the disease type. To overcome these challenges, we need a powerful deep learning model such as DenseNet121, which recognize small details at early stages.
The data-sets utilized in this research include rice leaf images related to three categories: Brown Spots, Leaf Stunt and healthy. These images are gathered from open access repository and a farming image database. The primary dataset is enlarged with the help of data augmentation techniques like brightness, flipping, translation, shearing and many more. This technique grows data-set diversity and helps the models to standardize the real-world conditions.

Literature Review:

Visual detection of rice leaf disease is very helpful for the agriculturist to identify the problem of rice plant at the initial stage, unaffected by some slow and inaccurate hand-operated inspection [13, 14]. Present researches use's model of deep learning, such as CNN and its architecture like "Dense Net" [15, 16]. These models recognize and discover leaf diseases like brown spots, leaf stunt, and bacterial blight [17]. Now these models have become more powerful and impactful by data expansion, massive volumes of data and ensemble learning [18, 19]. From 2020 onwards, this industry has been growing rapidly due to a large data set of real leaf images [20], efficient models that run on mobile device and approaches that enhance the accuracy [21, 22]. After all of this progress, there are still difficulties, which include restricted and uniform data sets, low yield potential in different locations and insufficient field-scale testing [3, 11].

Methodology:

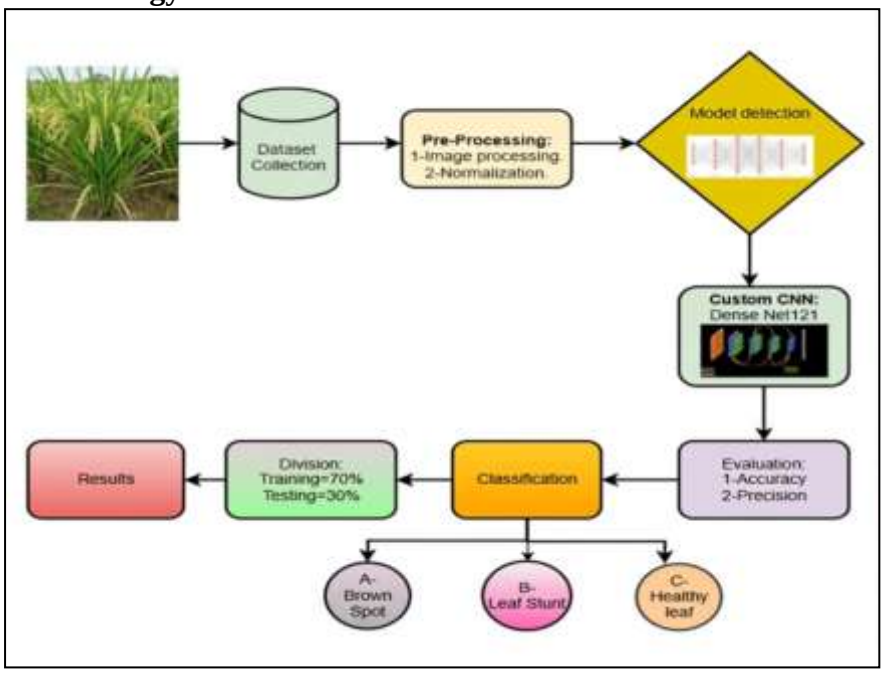


Figure 1: Flowchart illustrating the methodology

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Data Collection:

For every project related to AI and deep learning, data collection is an initial and essential step because the performance of machine learning models largely depends on the quality and diversity of training data [23]. In the case of rice leaf disease detection, first of all, different types of images are collected, such as leaves affected by different diseases and healthy leaves. Numerous images are collected to secure quality. Images should be clear so that they can represent different stages of diseases.

Table 1 Distribution of rice leaf image dataset

Disease Classes	Source	Total Images	Healthy Images	Diseased Images
Brown Spots	Kaggle, Public dataset, Local farms	500	0	180
Leaf Smut	Kaggle, Public dataset, Local farms	500	0	150
Healthy Leaf	Kaggle, Public dataset, Local farms	500	150	0

Table 1 **showing disease classes, image sources, and the number of healthy and diseased samples collected.**

Pre-processing:

Images collected from the previous step are prepared as a digital negative (raw image) for a deep learning model. Image processing enhances images by resizing, normalization and augmentation techniques to improve the quality of input data for deep learning models [4, 5]. Normalization of an image means scaling the image pixel values to a certain range [4]. A normalized image enhances contrast and consistency.

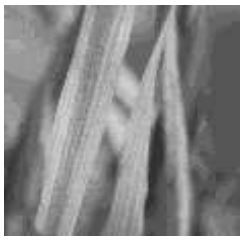
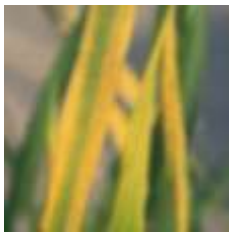
Table 2 Visualization of preprocessing methods used on rice leaf images prior to model training, such as histogram equalization, grayscale conversion and Gaussian smoothing.

Diseases	Equalized Image	Gray Scaled Image	Gaussian Blurred Image
Brown Spot			

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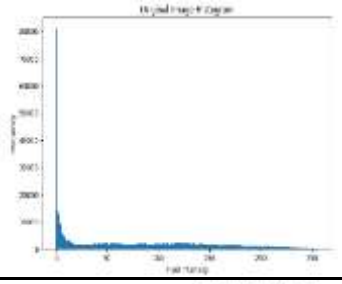
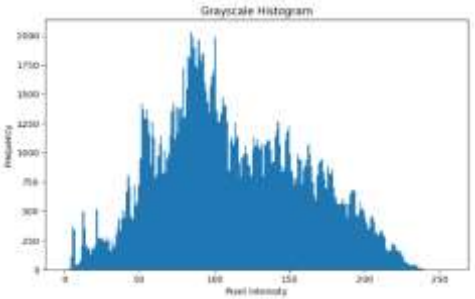
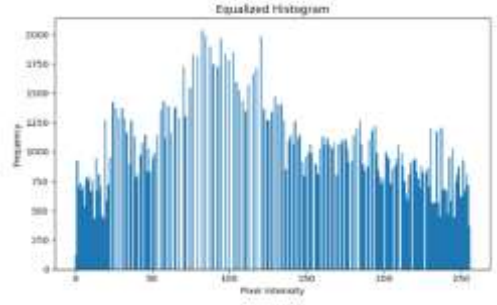
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Leaf Smut			
Healthy Leaf			

Graphical Representation:

Table 3: Figures of rice leaf image samples used in the dataset, depicting the visual nature of various types of diseases.

Images	Graph
	
	
	

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Augumentation of Data:
Through this step, the datasets are changed(increased) in size and diversity. Different augmentation techniques such as contrast adjustment, translation, flipping and shearing are used to increase the diversity of the dataset and improve model generalization [16, 24]. In this study, if we have 100 diseased leaf images, by applying augmentation techniques, we create almost 500-1200 new images with small distinctions.

Model Detection:
Deep learning models are widely used to detect and classify diseases in plant leaves by automatically extracting important visual features from images [8, 25]. It is a significant step where models understand patterns from the leaves and then identify the disease by comparing them with new images. Some deep learning models are CNN, ResNet50, VGG60, Mobile Net etc [9].

Custom CNN:
In this study, we use DenseNet, which is a powerful pretrained convolutional neural network architecture used for image classification tasks [9, 10]. In this deep neural network, each layer is interlinked to all previous layers. Load Dense Net with Image Net Weights, remove the top layer and now add a classification layer, which will indicate the disease in the rice leaf.

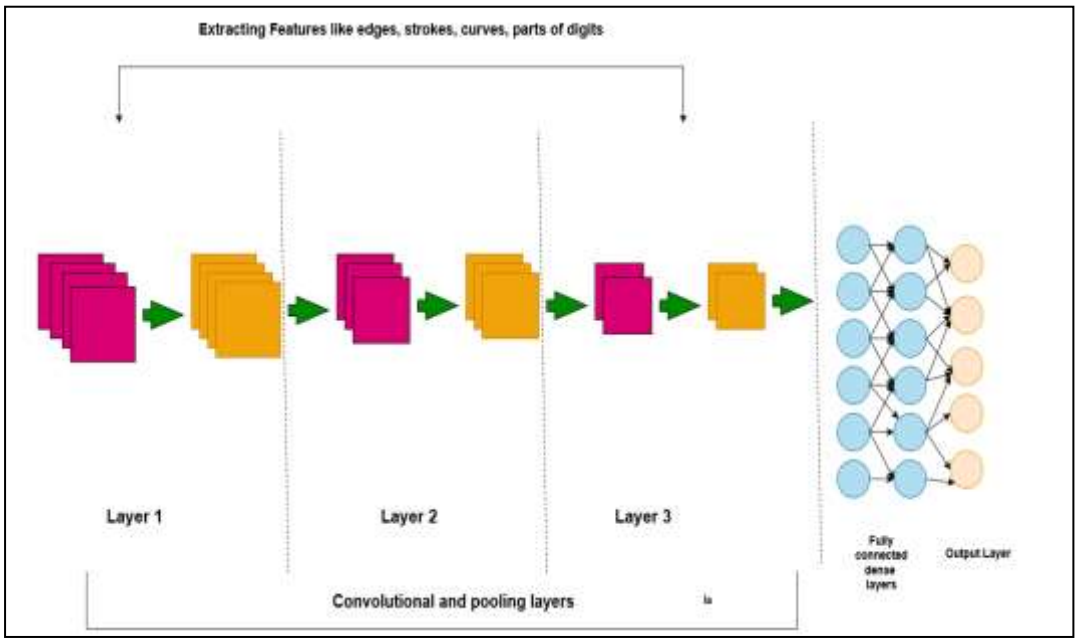


Figure 2: Schematic figure of the convolutional neural network architecture to be applied in the classification of rice leaf diseases, which demonstrates the process of feature extraction by a series of convolutional layers and the final classification by a series of fully connected layers.

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Evaluation:
Precision and accuracy are evaluated for the Dense Net model. Accuracy tells about the performance of the model on all rice leaf diseases. Similarly, precision indicates the disease type without mixing them because, in this case, rice leaf disease looks similar.

Classification:
In this phase, different leaf diseases are classified:

A-Brown Spot:
Brown circular spots appear on leaves. In some cases, there are also yellow holes.

B-Leaf Stunt:
It is due to viral and bacterial infections. Due to them, the leaves become short and pale green. Drying the tips of the leaves.

Healthy Leaves:
Leaves with no disease symptoms, no spots, no coloring and smooth texture.

Table 4: Samples of rice leaves belonging to three categories in which the disease is classified: Brown Spot, Leaf Smut, and Healthy Leaf. These visual dissimilarities allow the deep learning model to acquire disease-related trends in the process of training.

Brown Spot	Leaf Stunt	Healthy Leaf
		

Division:
This step evaluates how the model performs by dividing it into two categories: training and testing. Training shows how the model should be designed and learn disease patterns, shapes, texture and colors, and attributes of healthy and diseased leaves. In testing, the date is totally new, which is shown to the model. It indicates how the model works on new data (images).

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Data Processing Techniques:

The dataset used in this research includes rice leaf images expressing three main types: Brown Spot, Leaf Smut and Healthy Leaf. These images are collected from different public data repositories like "Kaggle" and local farm fields. All these datasets together contain 1500 images, almost every class of disease have equal number of images to maintain the dataset balanced. So the model does not support one class over the other. Images collected differ in disease intensity, background, resolution and radiance, verifying that the model understands effective and sound patterns ensuring that they correspond to real -world situations.

To improve the versatility of the model, the dataset is further enlarged with the help of "data augmentation" methods like zooming, flipping, rotating, translation and brightness. This measure helps to defeat hurdles like noise and lightning.

Before inserting these images into the AI and deep learning model, different preprocessing actions are applied to improve the uniformity and the quality of the images. Preprocessing steps include:

Normalization: It is used to stabilize the pixels of the images to upgrade model training.

Equation: To compress the pixel values of the images to a range between 0,1 with the help of min, max normalization.

$$\mathbf{I_{nor}} = \frac{\mathbf{I_{ori} - I_{min}}}{\mathbf{I_{max} - I_{min}}}$$

Here:

- $\mathbf{I_{nor}}$**:** It gives the output of normalized pixels of the image.
- $\mathbf{I_{ori}}$: It shows the original pixel intensity of the image.
- $\mathbf{I_{min}}$**:** It gives minimum pixel values of images.
- $\mathbf{I_{max}}$**:** It gives the maximum pixel values of the images.

Gaussian Blur: It reduces the noise without losing edges to make it smooth.

Equation:

$$\mathbf{G\ (p,\ q) = \frac{1}{2\pi\ \sigma^2}\ exp(p) - \left(\frac{p^2+q^2}{2\sigma^2}\right)}$$

Here:

- Sigma is used to handle the strength of blur.
- exp(p) represents "Euler's Number", e^x which is a mathematical constant.

Grayscale conversion: It is used to improve the contrast of the image for the analysis.

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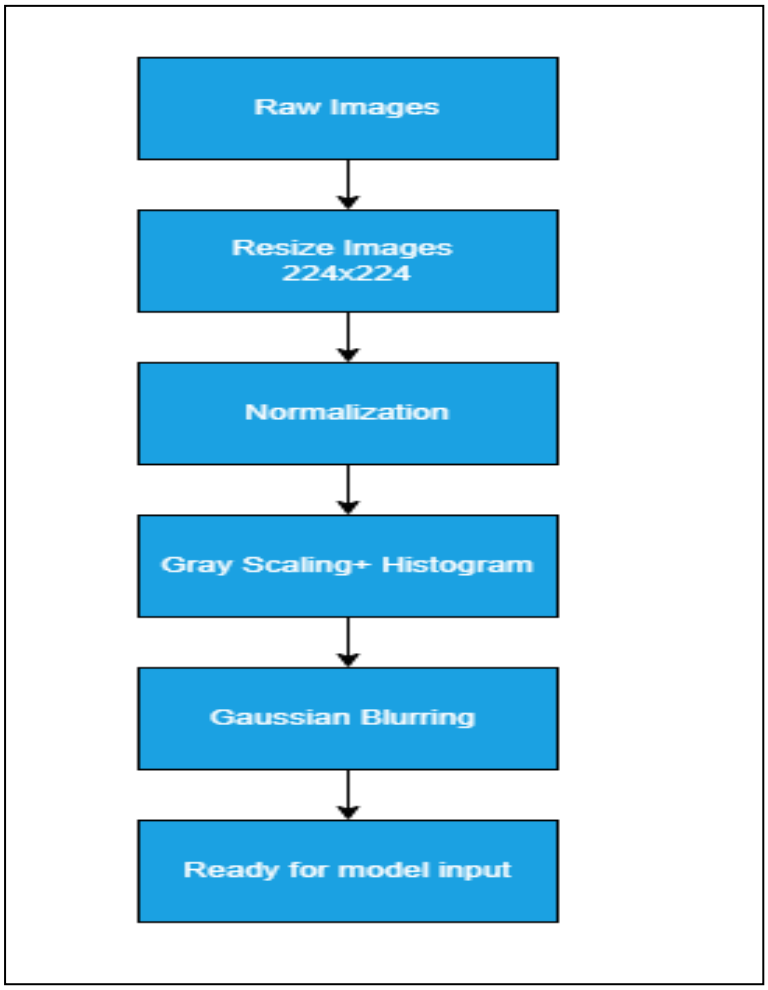


Figure 3: Preprocessing pipeline used to prepare rice leaf images for input into the DenseNet121 model.

The complete methodology follows the processing chain that starts with data collection, then pre-processing, augmentation, model training, evaluation and classification. Each step plays a crucial role in enhancing the performance of the model. Pre-processing guarantees quality enhancement, and augmentation makes the data smooth. DenseNet121 architecture is chosen due to its features like dense neural connectivity pattern and extraction ability.

Model Working with Equations:

DenseNet121 architecture is a convolutional neural network that emphasize on dense connectivity in which every layer gets input from the previous layer. This enhances features, transfers information better, and performs with fewer settings.

Dense Neural Connectivity Equation:

In this architecture, every layer gets the map of all other layers that come before it. The task performed at L- layer is as follows:

$$p_1 = H_L([p_0, p_1, p_2, p_3, \ldots\ldots\ldots, p_{L-1}])$$

Here:

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p_1 shows the output map of the L-layer.
H_L shows the scaling function implemented at layers that include convolution and batch normalization.
([p_0,p_1,p_2, p_3, … … … … , p_{L-1}]) show the series of maps from the previous layers.

Transition Layer Equation:

The number of feature maps are compress through the transition layer. It performs different tasks to lower geographical dimensions and to compress maps.

$$p_t = \theta(S*p)$$

Here:
p_t shows the transition layer output.
S shows the convolution filter of the model.
θ shows the compression factor.

Classification Layer Equation:

After moving through blocks and transition layer, the maps are averaged. Eventually, the images are classified into three main types: Brown Spots, Leaf Smut and healthy leaves.

$$Q=\varepsilon \frac{\varepsilon^{zi}}{\sum_{j=1}^{C} \varepsilon^{zi}}$$

Here:
z_i is the raw score given to the class.
C shows the complete number of classes. In this research total number of classes is 3.

Loss-Function:

The model used in this research is qualified with the help of "Categorical Cross-Entropy Loss".

$$L.F= -\sum_{i=1}^{C} p_i \log(p_i)$$

Here:
p_i means the verified label.
Signification of DenseNet121:
This architecture is well qualified for disease detection in rice plants due to:
It acquires fine-grained structures like colour changes, spots and many more.
Intense connections help to improve precision and reuse features.
It needs fewer frameworks while presenting strong performance.
This architecture lowers the exploding gradient problem.

Results:

The DenseNet121 convolutional neural network was used in testing the performance of the proposed rice leaf disease detection system. The dataset that was employed in this study was composed of rice leaf images that were classified into three categories: Brown Spot, Healthy Leaf, and Leaf Smut. The data was split into training and testing, where the model is able to learn the disease patterns during training and test its prediction ability using previously unseen images.
In order to determine the effectiveness of the model, a number of standard assessment

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scales were employed, among them, accuracy, precision, recall, and a confusion matrix analysis. These measures give a clear measurement of model performance. Accuracy gives the general percentage of samples that have been correctly classified, whereas precision and recall give the class-by-class information of the reliability of prediction and detection. Precision gives the number of predicted cases that are correct, and recall measures the number of predicted cases that are the real cases of disease.

Model Training Performance

The model was fine-tuned in the training phase when the prepared dataset was subjected to preprocessing and augmentation before being used on the DenseNet121 model. The model was able to improve its performance in learning over training cycles. The convergence in the training process was stable, showing that the model was able to learn meaningful visual features in rice leaf images.

During the training process, the model was taught to recognize some of the distinguishing visual features of rice diseases, including brown circular spots in brown spot disease, discolouration and pale green feel in brown spot disease, and the even normal feel on the healthy leaves. The deep convolutional layers of the DenseNet121 architecture were used to extract these features and enable the dense connectivity between layers, and enhance the reuse of features during training.

Classification Performance of DenseNet121

The assessment of the model was done using the test dataset once the training stage was over. The acquired evaluation metrics of the final classification are summarized in Table 5.

Table 5 Final classification performance of the DenseNet121 model

Class	Precision	Recall
Brown Spot	0.83	0.60
Healthy	0.67	0.80
Leaf Smut	0.86	0.80
Accuracy		0.79
Macro Average	0.79	0.73
Weighted Average	0.79	0.79

The DenseNet121 model had a total classification accuracy of 79% and proved to be able to detect the diseases of rice leaves with decent accuracy. The three classes gave the highest precision value (0.86), meaning that in cases where the model classified a leaf as infected with leaf smut, the model was correct in the majority of cases. This indicates that the deep learning model was able to find the visual patterns related to the leaf smut.

The healthy leaf category recorded the best outcome in terms of recall (0.80), which implies that most of the samples of healthy leaves that were presented to the model were accurately recognized by the model. This is especially significant in real-life agriculture since the correct identification of healthy leaves will prevent the needless use of pesticides and treatment of crops.

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The accuracy of the Brown Spot group was 0.83, yet the recall was lower at 0.60, meaning that some actual brown spot samples were not classified into the brown spot group, though predictions labelled as brown spot were too good. This can be explained by the visual similarities of brown spot symptoms to other patterns of the leaf, particularly during different lighting conditions or at initial stages of the disease.
In general, the balanced precision and recall values indicate that the model is consistent in performance across various disease categories.

Confusion Matrix Analysis

In order to further assess the classification behaviour of the DenseNet121 model, a confusion matrix was generated. The confusion matrix gives a clear depiction of what the model is predicting, displaying the correlation between the actual and predicted classes.

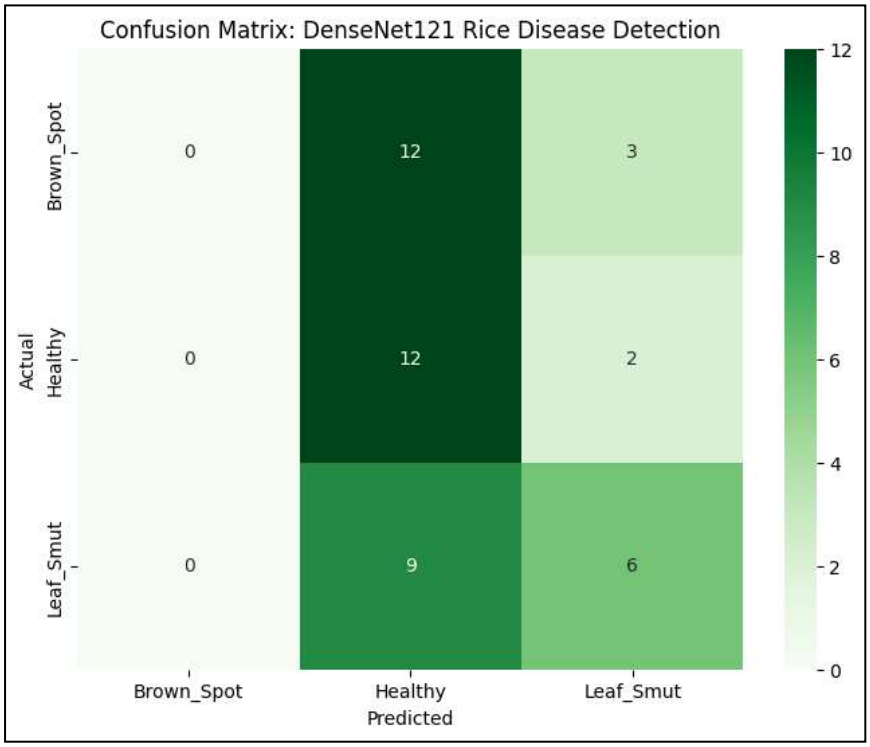


Figure 4: Confusion matrix illustrating the classification results of the DenseNet121 model

The confusion matrix shows that the model was able to correctly classify the majority of the healthy leaves. There were, however, instances of brown spot and leaf smut that were falsely forecasted as healthy leaves. This misclassification is typical of the plant disease detection problem since, at the initial stages of disease development, the symptoms can have an appearance similar to the normal patterns of leaves.
Although there are some minor mistakes, most of the predictions fall within the diagonal of the matrix, which is correct classifications. This shows that the model has been able to learn significant disease-related characteristics in the set.

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Final Confusion Matrix of the Fine-Tuned Model

Fine-tuning of the dense net121 model was used to create a second confusion matrix that would be used to examine the performance of the model with greater accuracy.

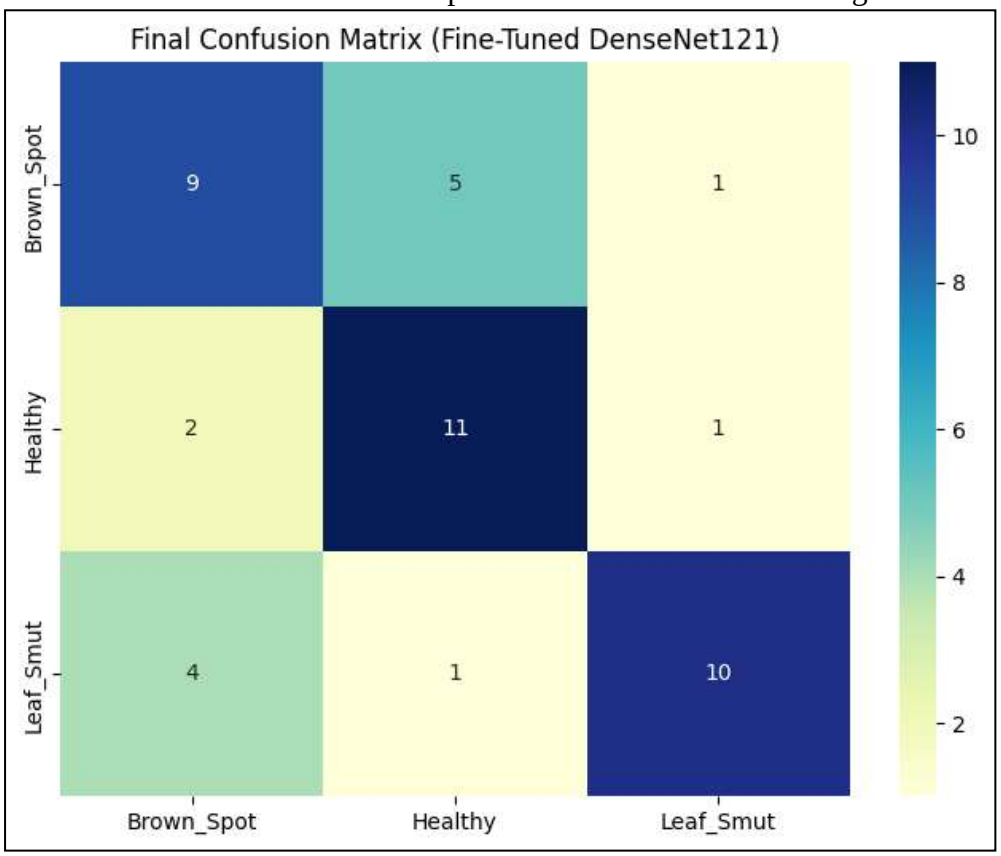


Figure 5 Final confusion matrix of the fine-tuned DenseNet121 model for rice leaf disease detection

The final confusion matrix shows that the model correctly classified:

9 samples of Brown Spot

11 samples of Healthy leaves

10 samples of Leaf Smut

The majority of the predictions are on the diagonal elements of the matrix, and this implies proper classification. There was, however, a certain degree of misclassification in the brown spots and the healthy leaves. This could be because of the overlapping visual characteristics, like the same colour intensity or initial signs of the disease that could not be easily differentiated, even among human eyes.

Conclusion

The primary aim of the study was to create a deep learning-based system that would automatically identify rice leaf diseases by means of image analysis methods. The experimental findings indicate that the DenseNet121 framework was able to extract pathology-related features and perform multi-class classification with reasonable accuracy.

The findings reveal that deep learning models have the potential of aiding automated plant disease diagnosis and will not depend on manual inspection techniques that are

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usually time-consuming and subject to human error. Even though a certain degree of misclassification was noted, the obtained accuracy of 79 per cent is an indication that the proposed system has great potential of being practically implemented in smart agriculture and crop monitoring systems.

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