Deep Learning-Driven Rice Leaf Disease Classification Using EfficientNet-B3

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Abstract-One of the most widely grown commodities in India is rice, and leaf diseases can seriously harm the overall quality and yield of the harvest. Because rice leaf diseases are closely related to food security and the economy, detecting them is crucial. The most prominent types of rice leaf diseases are Leaf Blast, Brown Spot, Tungro, and Bacterial Leaf Blight. To tackle this problem, we have researched several DL techniques for identifying leaf diseases using accuracy to measure output performance. This research benefits farmers and helps detect rice leaf diseases, which can improve overall crop yield. Deep learning model performance has been compared to other types of models. From our analysis of the DL models, we found that the EfficientNet-B3 technique performed the best, with an accuracy of 99%, followed by VGG16 and 5-layer convolution.

Index Terms— ***deep learning(DL), median filter, rice leaf diseases, CLAHE, convolutional neural networks(CNN), EfficientNet-B3.***

I. Introduction

Agriculture is a critical sector of the Indian economy and provides the primary source of income for an enormous number of people in India. [1]. Crop production is one of the primary players in determining the condition of the domestic market in India. Due to the increase in the population, climate change, and potential for instability in politics, agricultural businesses began to look for high-quality, low-cost products. To ensure food security and sustain a country's ability to produce food, it is essential to ensure that crops are healthy. There are many reasons for getting a plant sick, and many ways to measure how sick a crop is. Some of the reasons why crop production can be lost include: being infected. with disease, being located in an area where a disease spreads, and/or experiencing environmental changes that influence both the ability of a crop to produce and the final quality of a crop. The main factor that can contribute to soil contamination is not only treating a diseased crop using the proper pesticide early in the cycle of the plant disease, but also detecting the crop disease early.

There are many techniques to identify a plant disease before providing sufficient treatment; however, using the human eye is the traditional method of identifying disease currently being used, but that method is ineffective with regard to large acreage production [2]. This paper aims to develop a tool that will allow users to detect leaf diseases in rice crops early on and identify and name the specific diseases so that action can be taken to prevent damage. The rice plant (Oryza sativa) is among the most important GSP (Global South Producer) cereals in our nation. Rice has many uses and is rich in nutrients, having an estimated total annual production of over 104.80 million metric tons (1) across a range of Indian states (2). India, which ranks second globally in rice production, continues to see a year-on-year growth in the land area dedicated to rice cultivation. Rice is rich in starch, protein, soluble fibre, and much of the mineral content found in grains (3).

Plant pathogenic microorganisms (fungi, bacteria, viruses, and others) are responsible for most plant diseases. Rice leaf diseases caused by pathogens occur due to the effect of their environment on rice leaf; therefore, the possibility of rice leaf being infected with pathogen/, fungi, viruses, etc., is high (4).

Figure 1 illustrates some typical rice leaf diseases. The effects of climate change on pathogens will contribute to the creation of optimal growing conditions for pathogens. The initial stages of crop growth are often compromised due to fungal illnesses. While crops are actively growing, if they become ill due to a fungal disease, the crop will most likely diminish in yield.

Manually identifying illnesses on a large agricultural scale is a challenging task. In rice plants, farmers find it difficult to visually categorise a leaf disease (because they cannot see a disease without the assistance of an expert), and thus, will have to utilise the expertise of another individual to identify the specific disease, which takes additional time and costs money to perform. Rice leaves are predominantly susceptible to several widespread diseases, including Leaf Blast (LB), Bacterial Leaf Blight (BLB), Tungro and Brown Spot (BS). Therefore, controlling the rice leaf disease in early stages can safeguard both the yield and improve the quality of the green part of the rice leaf. For efficient rice disease management and rapid control, quick and precise disease detection is crucial. The use of digital image processing as well as deep learning networks is very effective and enables faster and more accurate disease detection. With progress in computer vision, there is a chance to utilise it to enhance and augment the protection of plants.

Figure (a): Bacterial Leaf Blight

Figure (b): Brown Spot

Figure (c): Leaf Blast

Figure (d): Tungro

Figure 1: Samples of Rice Leaf Disease Images

The paper is structured as follows: The previous methods for rice leaf disease detection are reviewed in Section II. Section III presents the materials and methods used to identify various kinds of rice leaf diseases. Finally, Section IV will summarise the experimental findings and future work in this field.

II Relate work

This study proposes an automated approach for perceiving diseases in groundnut leaves by leveraging ensemble learning techniques [3]. Their study examined a range of infected groundnut leaves to categorise four disease types, employing a hybrid approach integrating ML and DL. Based on the results of their analysis, they concluded that ResNet50 and DenseNet121 were the two architectures that provided the highest accuracy in prediction based on machine learning. Using data augmentation with either architecture gave an accuracy of 97.59 per cent. The greatest parsing speed associated with ResNet50 was achieved when used in conjunction with the LR model. This study presents an automated framework for detecting diseases in groundnut plants, where a deep learning technique was employed to increase both the precision and efficiency in detecting and classifying various disease-affected regions on the leaves [4]. The performance of the previously used algorithms is increased by using K-Nearest Neighbour in place of the classical Support Vector Machine classifier to distinguish between four distinct diseases: Bud Necrosis, Stem Rot, Leaf Spot, and Leaf Blight [5]. The purpose of this study is one of the common forms of leaf disease that groundnut trees face during their early life cycle and the proposed method includes four major phases of groundnut leaf disease recognition and categorization: (i) performing a colour enhancement on the input images; (ii) performing a planar separation; (iii) extracting features from the images; and (iv) implementing a backpropagation algorithm to detect the leaf disease [6]. In addition, the proposed research will carry out the detection of diseased plants in two phases. (1) Using a CNN, the type of crop and disease will be determined for each image, and (2) using the Keras frameworks and TensorFlow Lite, the digital image of the uploaded image will be classified against the dataset values to determine the disease classification of the uploaded image. The author concluded that the MobileNet model was the best-performing model among those tested for both classification and detection of rice crop plant diseases.

This study aims to make agriculture more sustainable by reducing the amount of pesticide needed to produce a higher-quality and more abundant harvest [7]. The researchers accomplished their objective by utilising image processing methods for feature extraction, followed by the application of Support Vector Machines to categorise the extracted features. Additionally, to improve model performance, data was augmented. In this investigation, the authors will identify three of the common rice plant diseases: BS, BLB and LB. This method will require the entire image to be input and can provide both the disease variant affecting the plant, as well as a percentage of accuracy from the classification of the given input by the model. [8], The author of this paper discussed the extraction of both colour and texture features of corn leaves while identifying the disease occurrence and determining the exact nature of the sickness present on the leaves. Binary and multi-class SVM classification were used to analyse the collected features. The maximum accuracy of this model was determined to be 85%. [9], This study investigated how to use deep learning to recognise and identify many different kinds of plant diseases. In terms of visually identifying and analysing plant illnesses, deep learning approaches are far better than traditional machine learning approaches.

In [2], Zekiwos, M et al., machine learning methods have been used to identify all steps in detecting a plant disease from start to finish; specifically, they used a CNN to categorise the diseased image of the leaf with high accuracy.

This paper reviews prior research related to automated agricultural practices, particularly identifying plant diseases. [10] compared using deep Convolutional Neural Networks (CNN) and conventional methods for identifying rice crop diseases by the number of training data points. Previous studies of cotton leaf pests and diseases [11] utilised similar methods but achieved a 96.4% success rate in matching specific conditions. Recent studies [12-19] have utilised similar CNN/deep learning/ computer vision methods to identify plant diseases, medicinal plant identification, detect insects, and quantify wheat heads. In addition, many current agricultural robots are programmed to use CNNs to independently identify plant leaf diseases and administer pesticides over those areas on large-scale farms, as well as measure and eliminate weeds within a pre-determined bounding box to apply herbicides.

III. Methodology

A. Datasets

The leaf dataset considered for this work consists of images of four types of rice leaf diseases. The data set consists of a total of 4000 images, comprised of respective numbers of 1000 images of each of the above-listed diseases (1000 Bacterial Leaf Blight, 1000 Tungro, 1000 Brown Spot, 1000 Leaf Blast). Each of the diseases is illustrated with 1 of each of the respective images listed in Table 1, and 1 example image from each disease is provided in the Figure. 1 below. Figure 2 is a flowchart depicting the proposed method.

Table 1. Details regarding the dataset's division

Type of Disease	Train Pictures	Test Pictures	Validation Pictures
Brown Spot	700	200	100
Bacterial Leaf Blight	700	200	100
Tungro	700	200	100
Leaf Blast	700	200	100

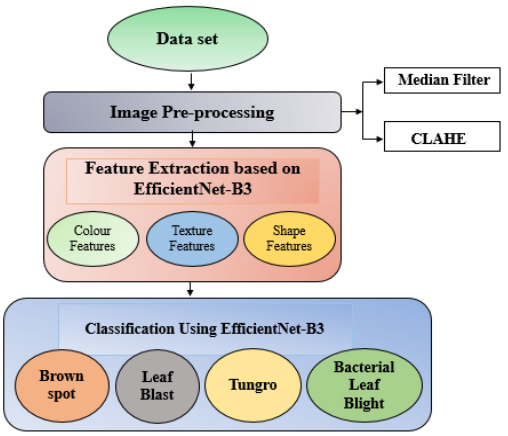

Figure 2: Flow diagram for the Proposed Technique

B. *Pre-processing Data*

The objective of data pre-processing in this research was to prepare good-quality images of rice leaves before training the deep-learning model. To remove noise while still preserving the structural edge of the leaves, we use a Median Filter to remove static noise in images. After this, CLAHE (Contrast Limited Adaptive Histogram Equalisation) enhances the contrast of the image and highlights spots of disease. The final stage is to assemble the images to be normalised for model training to provide the most accurate classification results.

C. *EfficientNet-B3:*

EfficientNet-B3 is a deep CNN chosen to create a model for classifying rice leaf images based on disease. The EfficientNet family includes EfficientNet-B3. EfficientNet-B3 performs the classification of rice leaf images into their corresponding disease categories by analysing and extracting meaningful features from the pre-processed images, including texture, colour, and disease-specific patterns. For the purpose of classifying diseases, these features will subsequently be transmitted to fully connected layers. Compared to traditional CNNs, EfficientNet-B3 requires a lower number of parameters, yet provides superior accuracy and efficiency when classifying images. A representation of the EfficientNet-B3 architecture is shown in Figure 3 below.

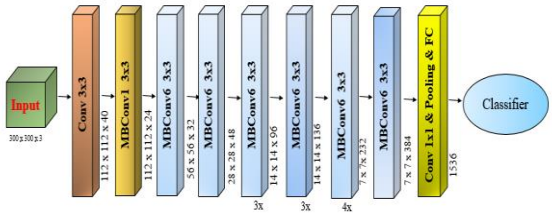

Figure 3: Architecture of EfficientNet-B3

The design of the EfficientNet-B3 Method includes the following layers:

- **Input Layer:** This is where the rice leaf image (resized) will enter the network for analysis and will consist of size 224 × 224 × 3 pixels.
- **Convolution Layer:** The important features will be detected by this layer. For example, the colour and texture of the rice leaves and any disease symptoms that are present within the rice leaf image.
- **MBConv Blocks (Mobile Inverted Bottleneck Convolution):** These are very efficient or optimised layers that are utilised to extract important features with a reduced number of parameters.
- **Batch Normalisation Layer:** A layer that helps to normalise the input to each of the preceding layers in an attempt to improve training speed and increase stability when training the model. The next layer of the Efficient Method is an Activation Function
- **(Swish/ReLU):** The incorporation of these activation functions adds non-linearity to the model, which substantially improves its capacity to learn complex patterns and relationships. The Swish is given in equation (1).
- **Global Average Pooling Layer:** This layer is responsible for transforming the complete feature map obtained from the preceding layer into a unified feature vector.
- **Fully Connected Layer:** The features extracted from this model will be used to classify rice disease.
- **Softmax Layer:** A Softmax Layer will provide a probability for each of the disease classes identified by the rice leaf image.
- **Output Layer:** This layer serves as the last component of the EfficientNet model, which is responsible for generating the ultimate predicted class of the rice leaf disease.

The Network architecture of the EfficientNet-B3 model used for rice disease classification is characterised by efficient feature extraction and high overall accuracy. A rice leaf image exhibiting visible disease symptoms is fed as input into the EfficientNet-B3 network for disease classification. As the initial step in the image classification process, a 3 x 3 Convolutional layer is employed to extract fundamental visual features from the rice leaf image. These basic visual features can consist of edges, colour changes, and texture. To create an accurate and efficient network, the architecture mirrors the principles of CNN Architecture by employing numerous Mobile Inverted Bottleneck Convolution (MBConv) blocks to extract features, thus using MBConv blocks allows you to obtain more complex and deeper feature maps (i.e., diseased regions and texture patterns of infected leaves and plant disease patterns at the leaf surface) while also allowing more efficient computation of the model. The two-dimensional feature maps reduce in size while the amount of feature dimensions (i.e. depth) increases through the use of MBConv blocks. Therefore, as the feature maps are generated and expanded within the neural network through the use of MBConv blocks, the model will begin to learn about the general characteristics of leaf disease. The extracted feature maps are compressed into a compact vector by using global average pooling, which is subsequently classified using a fully connected layer. After this, the rice leaf will be classified by the Softmax classifier given in equation (2) into one of the four considered classes based on the extracted features.

The equation for Swish can be written as:

$$f(x) = \frac{x}{1+e^{-x}} \quad (1)$$

Here $f(x)$ is the output, and x is the input value to the activation function.

The equation for softmax is.

$$P(y_i) = \frac{e^{x_i}}{\sum_{j=1}^{K} e^{x_j}} \quad (2)$$

Here K represents the total number of disease classes, and y_i represents the class i result score.

To train, a categorical cross-entropy loss function was employed, and Adam was the optimisation algorithm used to optimise the model based on Eq (3).

$$L = -\sum_{i=1}^{C} y_i \log(p_i) \quad (3)$$

Where y_i denotes the actual label of class I, p_i denotes the predicted probability allocated to class i by the proposed model, and the number of disease classes are represented by C.

IV Experimental Results

The datasets used to develop this framework encompassed 4,000rice leaf images influenced with Tungro, Leaf Blast, Bacterial Leaf Blight and Brown Spot disease symptoms, thus comprised both diseased and non-diseased rice plants, and were collected from open-source databases on Kaggle. The development dataset is divided into three subcategories, consisting of 10% for validation, and 20% for testing, 70% for training, to provide the model with a well-distributed and comprehensive dataset for the purposes of developing and validating the method. The dataset contains all publicly available datasets located on the Internet.

The hyperparameters with which the proposed EfficientNet-B3 model was trained to classify rice leaf diseases are presented in Table 2. Before giving them as inputs to the proposed model, the input images are first reduced in size to 224 × 224. Then, as a pre-processing technique, a Median Filter of 5 kernel size has been applied to remove background noise while still preserving significant edges within the leaf. The method was trained using the pre-trained weights of ImageNet, which aids with feature extraction within the model induced from previous training, therefore improving learning capabilities and thus speeding up the training time. During the final stage of classification, the model extracts 1536 output features that are then passed to the final output layer for classification. In the model, the Swish function is incorporated to enhance the efficiency of learning while being trained. For training and weight updates, the Adam optimiser with a learning rate of 0.0001 and cross-entropy loss was employed. The model received training at a batch size of 16 for five total epochs and was trained on either a GPU or CPU system, depending on usage at the time. The parameters listed have produced trained models that quickly and accurately classify examples.

Both the validation and training accuracies and losses graphs conclude that our disease classification model has successfully learned the disease characteristics associated with rice leaf images, as evidenced by an increasing trend in training accuracies per epoch, indicating that it is successfully learning what the disease characteristics are, as shown in Figures 4 and 5. The validation accuracy also indicates a similar increasing trend, establishing that our technique generalises well to previously unseen data. Both the training and validation loss decrease during the training phase; this indicates that our model is being optimised and that the proposed model converged satisfactorily due to decreasing stabilisation in validation losses after several training epochs. Therefore, our model can effectively identify rice leaf diseases, and the validation and learning accuracies indicate that our model is stable while learning to identify rice leaf diseases and testing of disease classification is presented in Table 3.

Table 2: Hyper Parameter

Parameter	Value
Input Image Size	224 × 224
Median Filter Kernel Size	5
Pre-trained	Yes (ImageNet)
Output Features	1536
Final Dense Layer	Linear(1536 → num-classes)
Activation	Swish
Function of Loss	Cross-Entropy Loss
Optimizer	Adam
Learning rate(lr)	0.0001
Size of Batch	16
Epochs	5
Device	GPU/CPU

Table 3: Testing Accuracy of Disease Classification

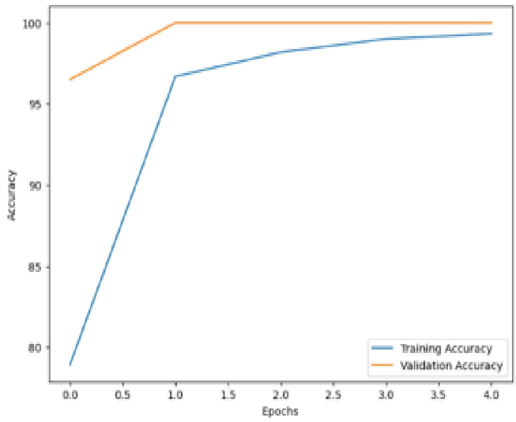

Figure 4: Training and Validation Accuracy Curves for Rice Leaf Disease Classification.

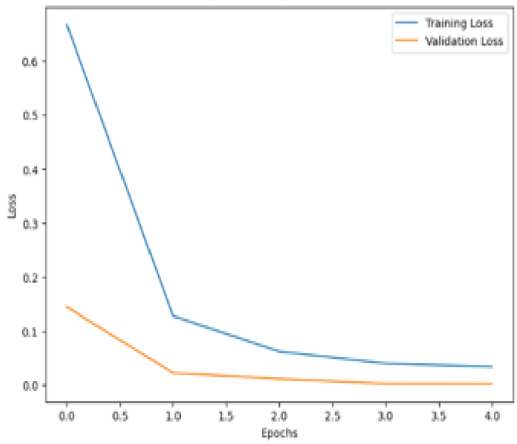

Figure 5: Training and Validation Accuracy and Loss Curves for Rice Leaf Disease Classification.

According to Table 4, several deep learning (DL) methods used to classify rice plant diseases have changing levels of accuracy. The VGG16 model had the least accurate results, at 58.40% accuracy, but this improved to 72.20% when three of the model's blocks were frozen. VGG19 had an accuracy of 72.40%, while Xception and ResNet50 both had results approximate to 72.20%. The five-layer convolutional model had the second-best results, at 78.20%. The EfficientNet-B3 model produced the highest level of accuracy, producing 99.83% accuracy for rice leaf disease classification; therefore, it is superior to the previously published methods listed below and seen in Figure 7.

A. Confusion Matrix

The confusion matrix obtained for the proposed work is presented in Figure 6. It provides the performance of classification of the proposed method on the four considered rice leaf disease classes. The diagonal entries of the matrix represent the number of rice leaf diseases as true positives, each with a total of 200 true positive classifications. There were zero false positive classifications included on the diagonal of the confusion matrix (i.e., the off-diagonal values), indicating that the proposed model effectively distinguished one rice leaf disease from another without any errors in classification. Based on this data, the proposed technique achieved exceptionally high levels of accuracy and reliability for classification purposes using the test dataset of rice leaf diseases.

Diseases	**Testing Accuracy**
Brown Spot	99.83%
Leaf Blast	99.98%
Bacterial Leaf Blight	99.66%
Tungro	99.99%

Existing Models	**Accuracy**
VGG 16 (With first 3 blocks of frozen)	72.2%
ResNet 50	72.2%
VGG 16	58.4%
5-Layer Convolution	78.2%
VGG 19	72.4%
Xception	72.2%
EfficientNet-B3 (Proposed Method)	**99.83%**

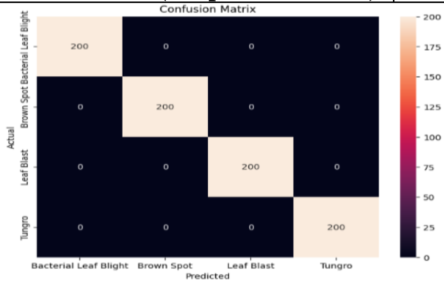

Figure 6: Confusion Matrix

Table 4: Accuracy of Different Existing Models

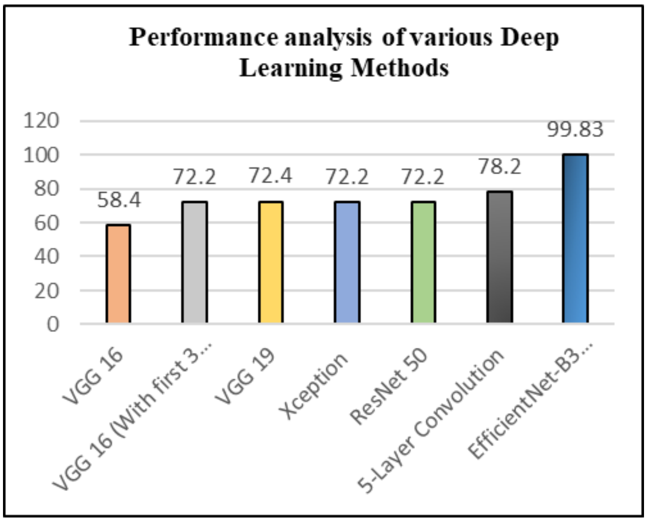

Figure 7: Accuracy of Different Existing Models

V Conclusion

The paper discusses a modern method for automatic recognition of different rice diseases through the use of the EfficientNet-B3 deep learning algorithm and rice images as inputs, thus allowing for grouping and classification of painted images and groups associated with all four rice diseases. With 99.83% accuracy, it is possible for producers to be able to identify disease/defects through the use of the image classification technique outlined in this paper. There is future potential to expand upon the proposed methodology by detecting other types of leaf diseases and implementing mobile and/or real-time monitoring solutions to support producers in utilising smart agriculture technologies to improve production efficiency. There is also an opportunity to increase both the robustness and accuracy of the method by training it with a larger dataset(s) in the future.

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