DETECTION OF RICE LEAF DISEASE USING CONVOLUTIONAL NEURAL NETWORKS

By

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DECLARATION

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MD. TAIMUR AHAD

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ABSTRACT

The increasing advancement of computer vision technology and recent advances in architectures in deep learning method has paved the way for computer assisted rice disease diagnosis using rice leaf's visible and invisible symptoms of disease. Though rice is an important food in the world, the computer mediated rice disease detection diagnosis based on digital images processing using deep learning method is under researched. Moreover, accuracy of rice disease detection using leaf is a challenge. To address the aforementioned challenges, this research, using a public rice disease dataset, we train a deep convolutional neural network (CNN) to identify rice diseases. In this study, DenseNet deep learning architecture was compared with other state-of-the-art CNN architecture EfficientNetB3, MobileNet, VGG16 and ResNet10. All the models were trained with original and augmented datasets having 120 and 34,980 images, respectively. The results suggest that DenseNet model achieved 99.22% accuracy and 98.42% precision in the evaluation dataset. Furthermore, the DensNet121 architecture provides superior result in recall and F measure value than other CNN models experimented in this research. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path toward smartphone-assisted crop disease diagnosis on a massive global scale. This research is significant as this study offers several critical applied contributions that can bring benefits to the Bangladeshi government and agriculture related stakeholders. The research focused deep learning method for disease detection in one of the under research herd crop: Rice which is the main food in many countries.

CONTENTS

LITERATURE REVIEW
ON

DETECTION OF RICE LEAF DISEASE USING CONVOLUTIONAL NEURAL NETWORKS

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The aim of the research is to increase the accuracy rate of rice disease detection using the leaves utilising the deep learning method namely Convolutional Neural Network (CNN). The research applies DenseNet121, EfficientNetB3, MobileNet, VGG16 and ResNet10 of CNN models to realise which models provides best accuracy rate in rice disease detection. Hence, the research is multi-domain and the literature review requires literates from CNN, disease of the rice crops and digital image processing applied in rice disease detection. We first introduce the readers to the CNN and its various networks. DenseNet121, EfficientNetB3, MobileNet, VGG16 and ResNet10 architectures are presented and discussed with the support of images. Then the discussion proceeds to the importance of rice as a crop in Bangladesh and various rice diseases. Lastly, we review the studies those applied computer mediated image processing technique to detect rice disease using leaves.

1. INTRODUCTION

Over the last decade, the advancement of computer vision technology and advent of novel algorithms in the digital image processing plays an increasingly important role in monitoring disease. The most remarkable achievement using digital image processing for plant disease is accuracy, speed of diagnosing the disease and predictions (Al-Zebari & Sengur (2019). Another important advantage is a more reliable solution than before. Therefore, recently, the advances of digital image processing techniques used in the plant leaf disease detection are an important research interest due to the improvement of machine vision system, computing hardware and non-tactile application.

Usually, diseased leaves are covered with spots, color, and diseased shape. Thus, diseased leaf provides an opportunity to perform image processing and to collect information on inconsistency among the pixels of the entire leaf. The inconsistency of plant leaves, thus provide information of disease (Mitkal et al. 2016). The digital image processing is the process of partitioning a digital image into multiple segments. Image segmentation is typically used to locate objects and boundaries in images (Tan, 2016). In other word, segmentation process partition images into sets of pixels, also known as superpixels. Segmentation process, then assigns a label to every pixel in an image. Some pixels with the same label share certain visual characteristics (Singh & Singh 2010). Each of the pixels in a region is expected to be similar with respect to any characteristic or computed property, such as color, intensity, or texture. However, in the case, where one pixel differs to other pixel, it provides information of inconsistency in the object or the presence of other objects. Realizing the applicability of image segmentation, the process is applied in disease, detection of betel vine (Piper BetleL.) by Dey, Sharma & Meshram (2016), Cotton Leaf Spot Diseases Detection Techniques by Revathi (2012), counting leaves in plant images by (Kumar & Domnic 2019).

Digital image processing has been also applied in the rice leaf disease detection by (Al-Bashish, Braik and Bani-Ahmad 2011); (Al-Hiary et al 2011); (Dhaygude Sanja, Kumbhar Nitin 2013); (Singh & Misra 2017). In digital image processing, deep neural network architectures with many processing layers and neurons is an efficient way to perform detection of rice plant disease. For example, recently, Chen et al. performed the detection of rice plant disease with a deep neural network of Convolutional Neural Network (CNN) (Chen et al., 2020c). Using CNN's VGGNet architecture, Chen et al. performed maize plant and rice plant disease classification (Chen et al., 2020d). . Chen et al. also proposed a new model namely MobileNet-Beta by expanding the pre-trained MobileNetV2 model for the detection of plant diseases called (Chen et al., 2020b). Too et al., reported that the DenseNet architecture of CNN the highest test accuracy with 99.75% (Too et al., 2019). Geetharamani and Pandian trained the 9-layer CNN architecture in the PlantVillage dataset and the model achieved 96.46% classification accuracy on the test dataset (Geetharamani and Pandian, 2019). Mohanty et al. (2016), on the other hand used AlexNet and GoogLeNet of CNN to classify classified plant diseases and obtained 99.35% classification accuracy (Mohanty et al., 2016). Using PlantVillage, Ferentinos's model of VGG architecture provided highest accuracy with 99.53% (Ferentinos, 2018).

The preliminary literature review suggests, there is an increase in the use of CNN as a deep learning architecture to detect plant leaf diseases. However, there are still gaps to be investigated regarding the use of CNN's various architecture to find efficient model. Therefore, this study aims to examine the success of the state-of-the-art CNN architectures such as AlexNet, ResNet50, VGG16 and InceptionV3 in classifying the rice plant disease detection. The ultimate goal is to reach the model that provides highest accuracy rate in classifying rice leaf disease detection.

2. PROBLEM DEFINITION AND MOTIVATION

Since Rice is the major crop, classification of disease in paddy is very important as it prevents the losses in the yields and quantity. However, once the diseases appear, it should be detected and identified in order to avoid loss by caring rice crops as soon as possible before they become more severe. This is the main motivation of conducting this research.

Another motivation to conduct the research is that rice disease detection is still primitive among the common farmers in Bangladesh. The existing method for rice disease detection is simply naked eye observation of experts through which identification and detection of rice diseases is done (Singh & Misra 2017). For doing so, a large team of experts as well as continuous monitoring is required. This is a costly process for the poor farmers or when the farms are large. At the same time, in some countries, farmers do not have proper facilities or even idea that they can contact with experts. Due to which consulting experts even cost, high as well as time consuming too. Plant disease identification by visual way is a more laborious task and at the same time, less accurate and can be done only in limited areas.

Whereas if automatic detection technique is used, it will take less effort, less time and become more accurate. In plants, some general diseases seen are brown and yellow spots, early and late scorch, and others are fungal, viral and bacterial diseases. Image processing is used for measuring the affected area of disease and to determine the difference in the color of the affected area (Singh & Misra 2017).

As seen from previous studies mentioned above, there is an increase in the use of deep learning architectures on the diagnosis of rice leaf diseases in the literature. However, there are still gaps to be investigated regarding the use of especially new deep learning architectures in plant leaf disease detection. Especially, the need for efficient models with fewer parameters, trained faster and without compromise on performance is inevitable.

The main purpose of this study is to examine the success of the state-of-the-art CNN architectures such as AlexNet, ResNet50, VGG16 and InceptionV3 in classifying the rice plant disease detection. The ultimate goal is to reach the model taht provides highest accuracy rate in classifying rice leaf disease detection.

Following the aim of the project, the following research question is proposed:

RQ: How rice leaf disease can be detected accurately using neural network data sets and improved algorithm of image segmentation?

3. LITERATURE REVIEW

This chapter reviews the research associated with the objective of this thesis. The aim of this research is to apply states-of-arts network models of CNN and to find the network that provides improved accuracy of rice leaf disease detection. Therefore, the review requires literature from CNN and its various network architectures and image processing technologies that applied in rice leaf disease detection.

2.2 Convolutional neural network

The Convolutional Neural Networks (CNN) is a deep learning method that has become one of the best image classification technique which has already acquired great success (Xu et al., 2017; Zhao & Jia, 2016; Sainath et al., 2015; Ribeiro et al., 2016; Ciresan et al., 2011; Kawasaki et al., 2015).

In contrast to Artificial Neural Network (ANN) which has a single layer, CNN has a number of layers placed in sequence. In detail, it consists of an input layer, many convolutional layers, pooling layers, fully connected layer and finally an output layer. Apart from the input and the output layer the rest of the layers are termed as hidden layers. CNN's are mostly used for image classification and recognition due to its high accuracy. Facebook, Google are few among the many who are using CNN for various face, image-related activities. CNN was used in various types of problems. Starting from object recognition tasks, human pose estimation, in natural language processing some of its implementations are text classification, emotion analysis, text translation, etc. (Fig.1).

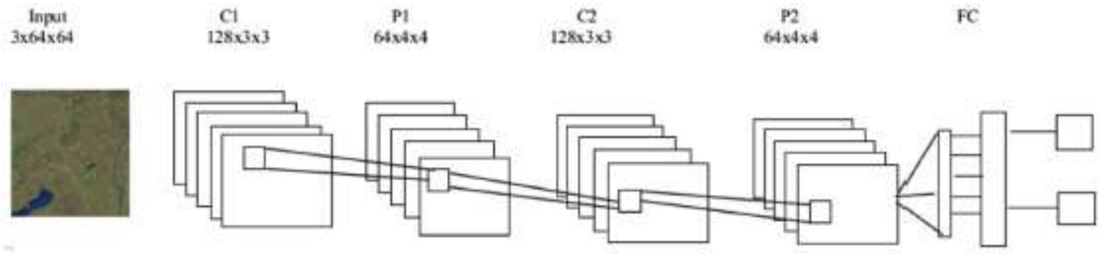

Figure 1: The CNN architecture

The term “convolution” refers to the mathematical combination of two functions to form a third function. When that happens, two sets of information are merged. In the context of CNNs, a convolutional layer (called filter or kernel) is applied to the input data to then produce a feature map (Figure 2) (Albawi, Mohammed & Al-Zawi 2017).

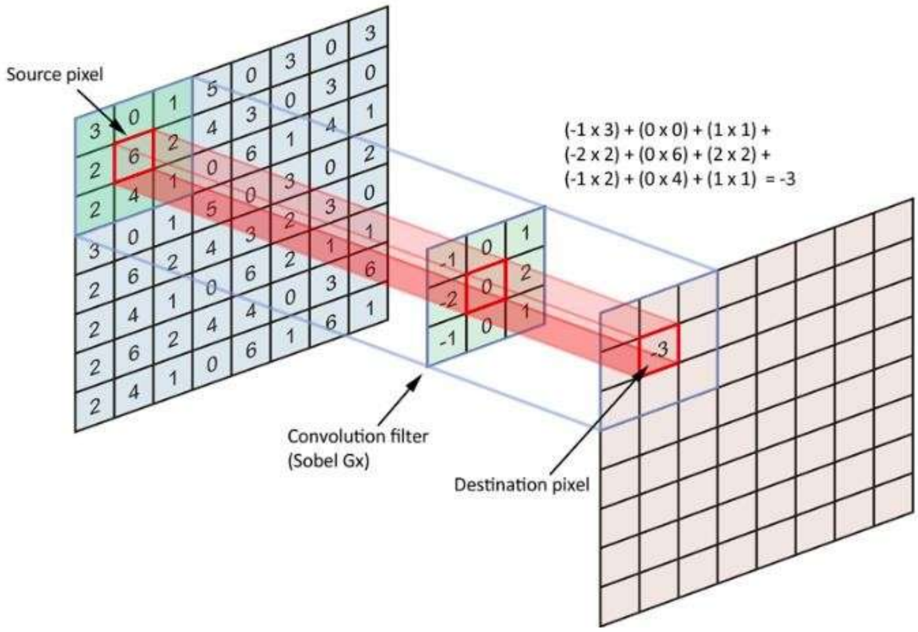

Figure 2: The filter slides over the input and performs its output on the new layer

2.1 State of the art CNN based models

The discussion of the various networks is presented in the next sections:

AlexNet

The AlexNet model is an 8-layer CNN architecture and the architecture follows the design of LeNet-5 (LeCun et al., 1989). This architecture uses ReLU activation function in the convolutional and fully connected layers. It has approximately 61 million parameters (Krizhevsky et al., 2012). The AlexNet architecture takes the input image size as 227 × 227. It is consists of five convolutional layers followed by three fully connected layers and finally the Softmax layer (see given in Fig. 2. 2) . The fully connected layer FC-8 of AlexNet architecture used in this study is connected to the Softmax layer with 39 neurons. Each output value in the Softmax layer is the ratio of the input image to the class represented by the corresponding output. The aim of Softmax layer is to generate a distribution using the inputs coming from the FC-8 layer and assigns a probability value for each class which of total is 1 for all classes.

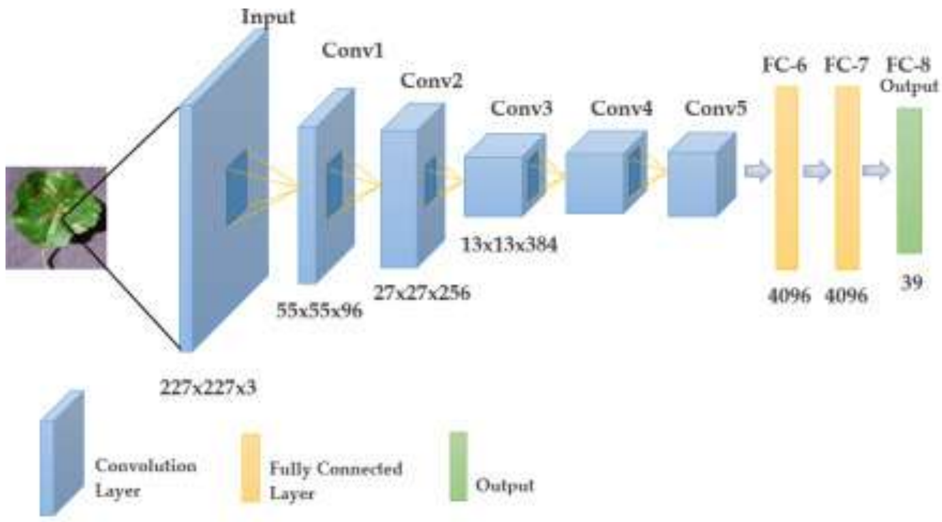

Figure 3: Schematic representation of AlexNet.

VGG16

VGG16 is a CNN architecture that contains 16 layers and the input layer takes images of 224×224 pixels. It has approximately 138 million parameters and instead of having large number of hyper-parameters, it always has the same convolution layers that use 3×3 filters with stride 1 and same padding and maximum pooling layers that use 2×2 filters with stride 2 (Simonyan and Zisserman, 2014). The VGG16 architecture follows this convolution and maximum pooling layers arrangement consistently throughout the entire architecture (see Figure 4). Finally, there are 3 FC layers first two with ReLU and the last with Softmax activation function.

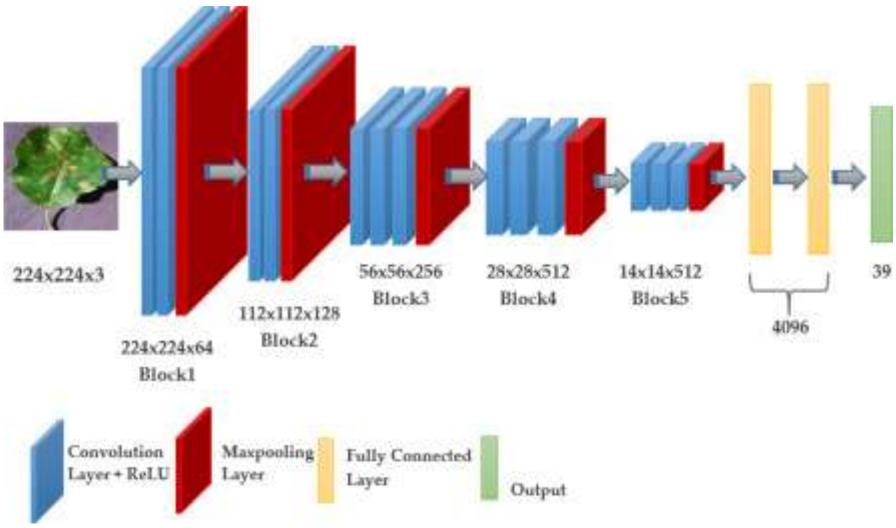

Figure 4: Schematic representation of VGG16.

ResNet50

ResNet50 architecture (He et al., 2016), which won the ILSVRC-2015 competition in 2015, is an architecture proposed to solve the problem of multiple non-linear layers not learning identity maps and degradation problem. ResNet50 is a network in network architecture based on many stacked residual units (Figure 5). Residual units are used as building blocks to build the network. These units consist of convolution and pooling layers. This architecture uses 3 × 3 filters as VGG16 and takes input images of 224 × 224 pixels.

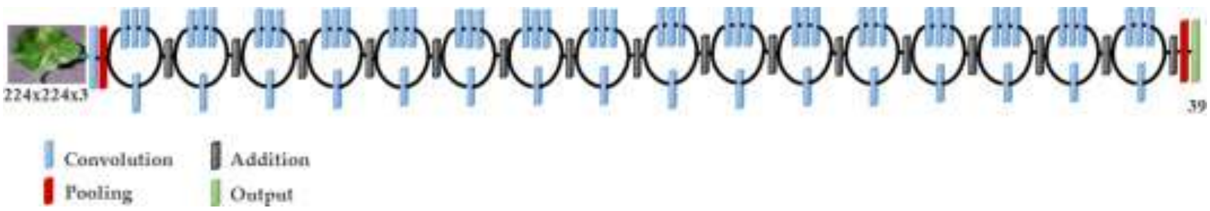

Figure 5: Schematic representation of ResNet50.

Inception V3

Inception V3 (Szegedy et al., 2016) developed by Google, is the third release in the Deep Learning Evolutionary Architectures series. After the Inception V1 architecture was developed by Szegedy, batch normalization was performed in Inception V2. Then the idea of factorization was introduced in Inception V3. The main purpose in factorization is to reduce the number of connections and parameters without reducing the efficiency of the network. The model itself consists of symmetrical and asymmetrical building blocks containing convolutions, average pooling, max pooling, concats, dropouts and fully connected layers (Figure 6). The Inception V3 architecture, which has the Softmax function in the last layer, consists of 42 layers in total and the input layer takes images of 299 × 299 pixels.

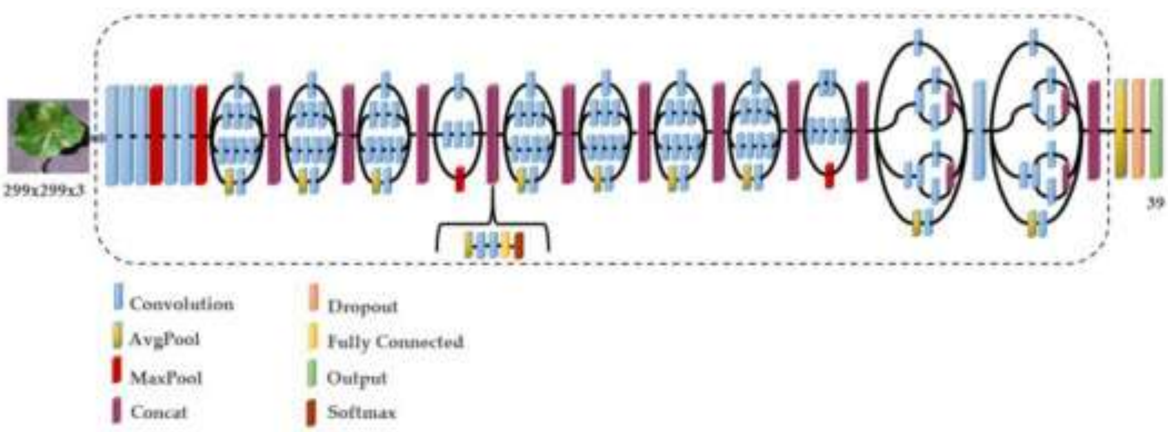

Figure 6: Schematic representation of Inception V3.

EfficientNet

Success has increased as the models used in the ImageNet dataset since 2012 have become more complex, but many are not effective in terms of computing load. EfficientNet model, which is among the state-of-the-art models by reaching 84.4% accuracy with 66 M parameter in the ImageNet classification problem, can be considered as a group of CNN models. EfficientNet group consists of 8 models between B0 and B7, and as the model number grows, the number of calculated parameters does not increase much, while accuracy increases noticeably. Unlike other CNN models, EfficientNet uses a new activation function called Swish instead of the Rectifier Linear Unit (ReLU) activation function (Tan and Le, 2019).

The aim of deep learning architectures is to reveal more efficient approaches with smaller models. EfficientNet, unlike other state-of-the-art models, achieves more efficient results by uniformly scaling depth, width, and resolution while scaling down the model. The first step in the compound scaling method is to search for a grid to find the relationship between the different scaling dimensions of the baseline network under a fixed resource constraint. In this way, a suitable scaling factor for depth, width and resolution dimensions is determined. These coefficients are then applied to scale the baseline network to the desired target network (Tan and Le, 2019).

The main building block for EfficientNet is the inverted bottleneck MBConv, which was first introduced in MobileNetV2 (Mark et al., 2018), but due to the increased FLOPS (floating point operations per second) budget, it is used slightly more than MobileNetV2. In MBConv, blocks consist of a layer that first expands and then compresses the channels, so direct connections are used between bottlenecks that connect much fewer channels than expansion layers. This architecture has in-depth separable convolutions that reduce calculation by almost k2 factor compared to traditional layers where k is the kernel size which denotes the width and height of the 2D convolution window (Mark et al., 2018). The schematic representation of EfficientNet B0 model is shown in Figure 7.

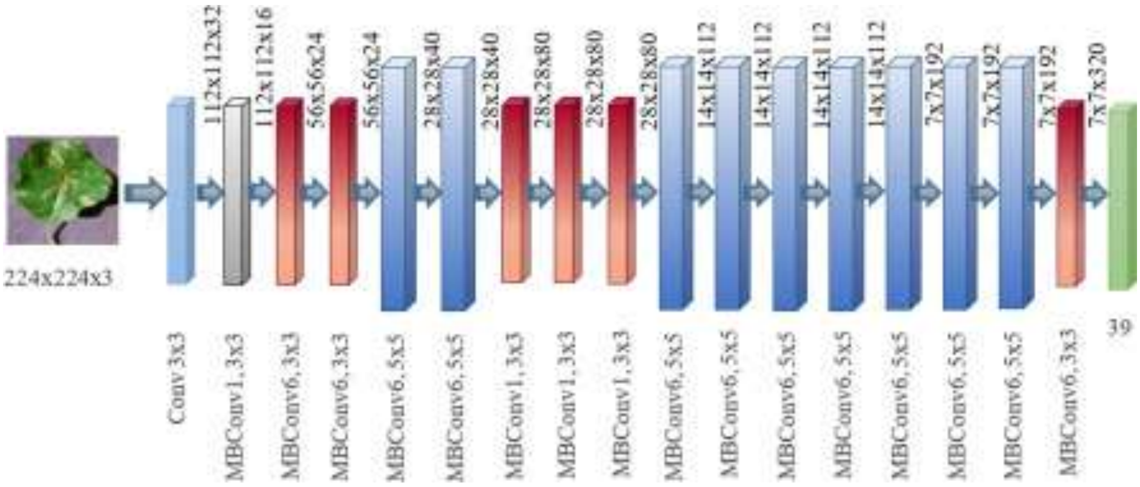

Figure 7: Schematic representation of EfficientNet

2.4 Importance of rice as a crop and diseases of rice

As a cereal grain, rice is the most widely consumed staple food for over half of the world's human population (Nguyen, 2020). Rice is the main crops in Bangladesh. Like many other developing countries rice is the major source of income for the rural people/farmers especially in Bangladesh. Therefore, when rice production is hindered due to rice disease, it impacts on the national economy. For example, Blast disease of rice causing 11-15% yield loss annually (Hossain, Ali, & Hossain 2017). Sarker et al. (2016) reported that Sheath blight (a rice disease caused by Rhizoctonia solani) affects the crop in almost every season in Bangladesh. The disease reduces quality as well as quantity of the crops which in turn affects the economy of the country like Bangladesh where agriculture is the main occupation.

Rice disease is an abnormal physiological process that distorts the rice plant's normal structure, growth and function. Among the diseases, Brown Spot (Helminthosporium oryzae), Sheath Rot (Sarocladium oryzae), Sheath Blight (Rhizoctonia Solani), False Smut (Ustilaginoidea virens), Grain discolouration (fungal complex), and Leaf streak (Xanthomonas oryzae pv. Oryzicola) are common rice diseases in Bangladesh. Below we present symptoms of the diseases (table 1):

Table 1: Various rice disease and infected leaves

Disease	Symptom	Image of diseased leaf	Reference
Rice false smut	Leaves are transformed into yellow or greenish velvety spore balls.		Nessa et al. (2018)
Sheath Blight	On the leaf sheath oval or elliptical or irregular greenish gray spots are formed. As the spots enlarge, the centre becomes greyish white with an irregular blackish brown or purple brown border.		Parveen, Hossain, & Ali (2018)
Blast disease of rice	Blast can occur wherever blast spores are present. The blast is the gray colored spot.		Hossain, Ali & Hossain, (2017); Khan et al. (2016).
Ufra	Ufra disease on deepwater rice, Bangladesh; note partial emergence and distorted panicles due to nematode infection.		Khanam et al. (2016)
Calcium deficiency of rice	tips of youngest leaves become white or bleached, rolled, and curled. Old leaves eventually turn brown		Naila et al. (2019). .

2.5 Rice disease detection using digital image processing technologies

The literature review suggests that four approaches are used for the automatic diagnosis of rice diseases.

The first approach for automatic rice disease detection is conventional means such as pattern recognition techniques (Phadikar & Sil, 2008; Rahman et al., 2020). Following this approach, Phadikar & Sil (2008) proposed a rice disease identification approach where the diseased rice images were classified utilizing Self Organizing Map (SOM) (via neural network) in which the train images were obtained by extracting the features of the infected parts of the leave while four different types of images were applied for testing purposes. A somewhat satisfactory classification results were reported. Islam et al (2018) study presents a new technique using only one feature i.e. RGB values to detect and classify the diseases based. The disease is based on percentage of RGB value of the affected portion using image processing. Once the percentage of RGB from the affected region is extracted and grouped into various classes, they are fed to a simple classifier called Naive Bayes which classifies the disease into various categories. This technique has successfully detected and identified three rice diseases, namely rice, brown spot, rice bacterial blight, and rice blast. This technique is efficient and faster because it uses only one feature i.e. RGB values of the affected portion which requires minimum computation time to identify and classify the diseases. Rather than processing the whole leaf, this technique even successfully detects the diseases using only a small sample of a leaf containing the affected portion of rice disease.

The second method is using support vector machine. For example, Phadikar, Sil & Das, 2012; Prajapati, Shah & Dabhi, 2017 utilized this method. Phadikar, Sil & Das (2012) proposed an automated approach to classify the rice plant diseases, namely leaf brown spot and the leaf blast diseases based on the morphological changes. A total of 1,000 spot images captured by Nikon COOLPIX P4 digital camera from a rice field were used. The results obtained were 79.5% and 68.1% accuracies from the Bayes' and SVM classifiers, respectively. Support Vector Machine (SVM) technique was also utilized by Prajapati, Shah & Dabhi (2017) for multi-class classification to identify three types of rice diseases (bacterial leaf blight, brown spot, and leaf smut). The images of infected rice plants were captured using a digital camera from a rice field and obtained 93.33% accuracy on training dataset and 73.33% accuracy on the test dataset.

Thirdly, digital image processing techniques by Arnal Barbedo, 2013; Zhou et al., 2013; Sanyal et al., 2008; Sanyal & Patel, 2008 Study. For example, Zhou et al. (2013) investigated a technique to evaluate the degree of hopper infestation in rice crops where a fuzzy C-means algorithm was used to classify the regions into one of four classes: no infestation, mild infestation, moderate infestation and severe infestation. Their study illustrated that the accuracy reached 87% to differentiate cases in which rice plant-hopper infestation had occurred or not whilst the accuracy to differentiate four groups was 63.5 %. Sanyal et al. (2008) proposed an approach for detecting and classifying six types of mineral deficiencies in rice crops where each kind of feature (texture and color) was submitted to its own specific multi-layer perceptron (MLP) based neural network. Both networks consist of one hidden layer with a different number (40 for texture and 70 for color) of neurons in the hidden layer where 88.56% of the pixels were correctly classified. Similarly, the same authors proposed another similar work (Sanyal & Patel, 2008) where two kinds of diseases (blast and brown spots) that affect rice crops were successfully identified.

The fourth approach is the texture analysis and feature extraction using computer vision for enhancing the accuracy and rapidity of diagnosing the results. Asfarian et al. (2014) developed a new approach of texture analysis to identify four rice diseases (bacterial leaf blight, blast, brown spot and tungro virus) using fractal Fourier. In their proposed study, the image of the rice leaf was converted to CIELab color space and the system was able to achieve an of accuracy 92.5%. The feature extraction from diseased and unaffected leaf images, the gray level co-occurrence matrix (GLCM) and the color moment of the leaf lesion region were implemented by Ghyar & Birajdar (2018) to create a 21-D feature vector and related features. The redundant features were eliminated with the genetic algorithm-based feature selection method to generate 14-D feature vectors to minimize complexity. The technique has shown a promising result; however, to improve its detection accuracy there is need for more optimization procedure to take place. The rice disease from the brown spot and blast diseases was described utilizing the color texture of rice leaf photos by Sanyal & Patel (2008). However, the technological standard of identification of rice diseases needs to be strengthened.

In Phadikar & Sil (2008), the entropy-based bipolar threshold technique was employed for segmentation of the image after improving its brightness and contrast. The author sought to integrate the image processing and soft computing technique for the detection of rice plant attacked by several types of diseases. The idea behind the technique was robust when utilized effectively. However, the average accuracy of identification on the four datasets was 82 percent which indicates that more enhancement is still required. The image processing and machine learning methods were utilized to non-destructively screen seedlings with rickets by Chung et al. (2016). Moreover, genetic algorithms were employed to develop SVM classifiers in order to optimize feature selection and model parameters for differentiating healthy seedlings and infected ones. The overall accuracy achieved in their study was 87.9 percent. However, since various diseases may have several symptoms, this approach should be tested if it is needed to use in other diseases, suggesting that this procedure has some limitations.

The final approach is moving towards deep learning models in an effort to detect diseases in various plants The Convolutional Neural Networks (CNN) is a deep learning method that has become one of the best image classification technique which has already acquired great success (Xu et al., 2017; Zhao & Jia, 2016; Sainath et al., 2015; Ribeiro et al., 2016; Ciresan et al., 2011; Kawasaki et al., 2015).

Chen et al. performed the detection of rice plant disease with a deep neural network of Convolutional Neural Network (CNN) (Chen et al., 2020c). Using CNN's VGGNet architecture, Chen et al. performed maize plant and rice plant disease classification (Chen et al., 2020d). . Chen et al. also proposed a new model namely MobileNet-Beta by expanding the pre-trained MobileNetV2 model for the detection of plant diseases called (Chen et al., 2020b). Too et al., reported that the DenseNet architecture of CNN the highest test accuracy with 99.75% (Too et al., 2019). Geetharamani and Pandian trained the 9-layer CNN architecture in the PlantVillage dataset and the model achieved 96.46% classification accuracy on the test dataset (Geetharamani and Pandian, 2019). Mohanty et al. (2016), on the other hand used AlexNet and GoogLeNet of CNN to classify classified plant diseases and obtained 99.35% classification accuracy (Mohanty et al., 2016). Using PlantVillage, Ferentinos's model of VGG architecture provided highest accuracy with 99.53% (Ferentinos, 2018).

Lu et al. (2017b) study has experimented the automatic identification and diagnosis of rice diseases using CNN as deep learning method. Using a dataset of 500 natural images of diseased and healthy rice leaves and stems captured from rice experimental field, CNNs are trained to identify 10 common rice diseases. Under the 10-fold cross-validation strategy, the proposed CNNs-based model achieves an accuracy of 95.48%.

Zhou et al. (2019) suggested Faster R-CNN approach, which seems to be ideal for the detection of rice diseases due to its good speed and high accuracy. Shrivastava et al. (2019) also applied CNN, for rice plant disease classification using transfer learning of deep convolution neural network. Using AlexNet CNN model, the model is able to classify rice diseases with classification accuracy of 91.37%.

Another method suggested by Ren et al. (2017) was capable of detecting plant diseases as well as enhancing the accuracy using Faster R-CNN. However, it is required to reduce the time for disease identification in order to allow it to be suitable for monitoring large-scale cultivation.

In a recent study, Rahman et al. (2020) developed a CNN approach for detecting diseases and pests (five classes of diseases, three classes of pests and one class of healthy plant and others) from rice plant images. A total number of 1,426 images were collected that were captured using four different types of cameras and the system achieved a mean validation accuracy of 94.33 %.

Rahman et al. (2020) suggested a new stacked CNN architecture which uses two-stage training to substantially reduce the model size while retaining high classification accuracy. The CNN architectures such as MobileNet, NasNet Mobile and SqueezeNet. Experimental results show that the proposed architecture can achieve the desired accuracy of 93.3% with a significantly reduced model size (e.g., 99% smaller than VGG16).

4. KNOWLEDGE GAP IN RICE LEAF DETECTION USING IMAGE PROCESSING

Though, the methods for automatic rice disease diagnosis based on digital images processing have received special attention, earlier, Islam (2018) identified Rice leaf disease detection using deep learning method is under researched. Bari et al. (2021) has criticized for low accuracy rate of rice disease detection models. Our literature review supports Bari et al. (2021), as most methods in this literature review reported classification accuracies between 50% and 95%. Those achieving higher accuracies were usually tested with fewer diseases and, in most cases, only one plant species. Those methods may not hold such a good performance when more diseases are added or other plant species are considered. More considerations about this problem can be found in Barbedo (2016).

Despite the fact there are several architectures available in CNN, most studies utilized one network rather comparing the accuracy using several architecture. Our this findings also supports Atila et al. (2021) that advocates novel deep learning architectures in rice leaf disease detection is yet to be implemented. Earlier, Barbedo (2016) also complained that there is a lack of methods that can be used under the real, uncontrolled conditions found in the field. Moreover, the gap between the current capabilities of image-based methods for automatic rice disease identification and the real-world needs is still wide (Barbedo, Koenigkan & Santos 2016).

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JOURNAL PAPER

Rice disease detection using leaves: performance comparison of CNN architectures

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Abstract

The increasing advancement of computer vision technology and recent advances in architectures in deep learning method has paved the way for computer assisted rice disease diagnosis using rice leaf's visible and invisible symptoms of disease. Though rice is an important food in the world, the computer mediated rice disease detection diagnosis based on digital images processing using deep learning method is under researched. Moreover, accuracy of rice disease detection using leaf is a challenge. To address the aforementioned challenges, this research, using a public rice disease dataset, we train a deep convolutional neural network (CNN) to identify rice diseases. In this study, DenseNet deep learning architecture was compared with other state-of-the-art CNN architecture EfficientNetB3, MobileNet, VGG16 and ResNet10. All the models were trained with original and augmented datasets having 120 and 34,980 images, respectively. The results suggest that DenseNet model achieved 99.22% accuracy and 98.42% precision in the evaluation dataset. Furthermore, the DensNet121 architecture provides superior result in recall and f1 value than other CNN models considered in this research. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path toward smartphone-assisted crop disease diagnosis on a massive global scale. This research is significant as this study offers several critical applied contributions that can bring benefits to the Bangladeshi government and agriculture related stakeholders. The research focused deep learning method for disease detection in one of the under research herd crop: Rice which is the main food in many countries.

Keywords: Plant disease, Leaf image, Deep learning, Transfer learning

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1. Introduction

Over the last decade, the advancement of computer vision technology and advent of novel algorithms in the digital image processing plays an increasingly important role in monitoring disease. The most remarkable achievement using digital image processing for plant disease is accuracy, speed of diagnosing the disease and predictions (Al-Zebari & Sengur (2019). Another important advantage is a more reliable solution than before. Therefore, recently, the advances of digital image processing techniques used in the plant leaf disease detection are an important research interest due to the improvement of machine vision system, computing hardware and non-tactile application.

Usually, diseased leaves are covered with spots, color, and diseased shape. Thus, diseased leaf provides an opportunity to perform image processing and to collect information on inconsistency among the pixels of the entire leaf. The inconsistency of plant leaves, thus provide information of disease (Mitkal et al. 2016). The digital image processing is the process of partitioning a digital image into multiple segments. Image segmentation is typically used to locate objects and boundaries in images (Tan, 2016). In other word, segmentation process partition images into sets of pixels, also known as superpixels. Segmentation process, then assigns a label to every pixel in an image. Some pixels with the same label share certain visual characteristics (Singh & Singh 2010). Each of the pixels in a region is expected to be similar with respect to any characteristic or computed property, such as color, intensity, or texture. However, in the case, where one pixel differs to other pixel, it provides information of inconsistency in the object or the presence of other objects. Realizing the applicability of image segmentation, the process is applied in disease, detection of betel vine (Piper BetleL.) by Dey, Sharma & Meshram (2016), Cotton Leaf Spot Diseases Detection Techniques by Revathi (2012), counting leaves in plant images by (Kumar & Domnic 2019).

Digital image processing has been also applied in the rice leaf disease detection by (Al-Bashish, Braik and Bani-Ahmad 2011); (Al-Hiary et al 2011); (Dhaygude Sanja, Kumbhar Nitin 2013); (Singh & Misra 2017). In digital image processing, deep neural network architectures with many processing layers and neurons is an efficient way to perform detection of rice plant disease. For example, recently, Chen et al. performed the detection of rice plant disease with a deep neural network of Convolutional Neural Network (CNN) (Chen et al., 2020c). Using CNN's VGGNet architecture, Chen et al. performed maize plant and rice plant disease classification (Chen et al., 2020d). . Chen et al. also proposed a new model namely MobileNet-Beta by expanding the pre-trained MobileNetV2 model for the detection of plant diseases called (Chen et al., 2020b). Too et al., reported that the DenseNet architecture of CNN the highest test accuracy with 99.75% (Too et al., 2019). Geetharamani and Pandian trained the 9-layer CNN architecture in the PlantVillage dataset and the model achieved 96.46% classification accuracy on the test dataset (Geetharamani and Pandian, 2019). Mohanty et al. (2016), on the other hand used AlexNet and GoogLeNet of CNN to classify classified plant diseases and obtained 99.35% classification accuracy (Mohanty et al., 2016). Using PlantVillage, Ferentinos's model of VGG architecture provided highest accuracy with 99.53% (Ferentinos, 2018).

The preliminary literature review suggests, there is an increase in the use of CNN as a deep learning architecture to detect plant leaf diseases. However, there are still gaps to be investigated regarding the use of CNN's various architecture to find efficient model. Therefore, this study aims to examine the success of the state-of-the-art CNN architectures such as AlexNet, ResNet50, VGG16 and InceptionV3 in classifying the rice plant disease detection. The ultimate goal is to reach the model that provides highest accuracy rate in classifying rice leaf disease detection.

2. Problem definition and motivation

Since Rice is the major crop, classification of disease in paddy is very important as it prevents the losses in the yields and quantity. However, once the diseases appear, it should be detected and identified in order to avoid loss by caring rice crops as soon as possible before they become more severe. This is the main motivation of conducting this research.

Another motivation to conduct the research is that rice disease detection is still primitive among the common farmers in Bangladesh. The existing method for rice disease detection is simply naked eye observation of experts through which identification and detection of rice diseases is done (Singh & Misra 2017). For doing so, a large team of experts as well as continuous monitoring is required. This is a costly process for the poor farmers or when the farms are large. At the same time, in some countries, farmers do not have proper facilities or even idea that they can contact with experts. Due to which consulting experts even cost, high as well as time consuming too. Plant disease identification by visual way is a more laborious task and at the same time, less accurate and can be done only in limited areas.

Whereas if automatic detection technique is used, it will take less effort, less time and become more accurate. In plants, some general diseases seen are brown and yellow spots, early and late scorch, and others are fungal, viral and bacterial diseases. Image processing is used for measuring the affected area of disease and to determine the difference in the color of the affected area (Singh & Misra 2017).

As seen from previous studies mentioned above, there is an increase in the use of deep learning architectures on the diagnosis of rice leaf diseases in the literature. However, there are still gaps to be investigated regarding the use of especially new deep learning architectures in plant leaf disease detection. Especially, the need for efficient models with fewer parameters, trained faster and without compromise on performance is inevitable.

The main purpose of this study is to examine the success of the state-of-the-art CNN architectures such as AlexNet, ResNet50, VGG16 and InceptionV3 in classifying the rice plant disease detection. The ultimate goal is to reach the model taht provides highest accuracy rate in classifying rice leaf disease detection.

Following the aim of the project, the following research question is proposed:

RQ: How rice leaf disease can be detected accurately using neural network data sets and improved algorithm of image segmentation?

3. Literature review

This chapter reviews the research associated with the objective of this thesis. The aim of this research is to apply states-of-arts network models of CNN and to find the network that provides improved accuracy of rice leaf disease detection. Therefore, the review requires literature from CNN and its various network architectures and image processing technologies that applied in rice leaf disease detection.

3.1 Convolutional neural network:

The Convolutional Neural Networks (CNN) is a deep learning method that has become one of the best image classification technique which has already acquired great success (Xu et al., 2017; Zhao & Jia, 2016; Sainath et al., 2015; Ribeiro et al., 2016; Ciresan et al., 2011; Kawasaki et al., 2015).

In contrast to Artificial Neural Network (ANN) which has a single layer, CNN has a number of layers placed in sequence. In detail, it consists of an input layer, many convolutional layers, pooling layers, fully connected layer and finally an output layer. Apart from the input and the output layer the rest of the layers are termed as hidden layers. CNN’s are mostly used for image classification and recognition due to its high accuracy. Facebook, Google are few among the many who are using CNN for various face, image-related activities. CNN was used in various types of problems. Starting from object recognition tasks, human pose estimation, in natural language processing some of its implementations are text classification, emotion analysis, text translation, etc. (Figure 1).

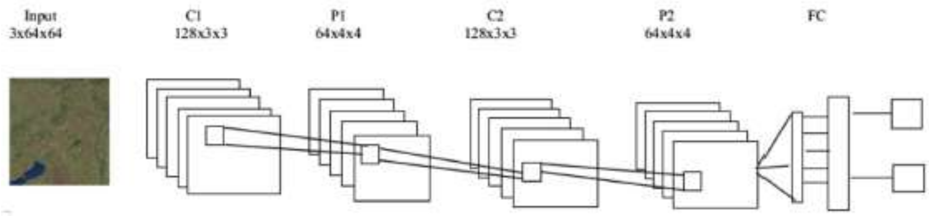


Figure 1: The CNN architecture

The term “convolution” refers to the mathematical combination of two functions to form a third function. When that happens, two sets of information are merged. In the context of CNNs, a convolutional layer (called filter or kernel) is applied to the input data to then produce a feature map (Figure 2) (Albawi, Mohammed & Al-Zawi 2017).

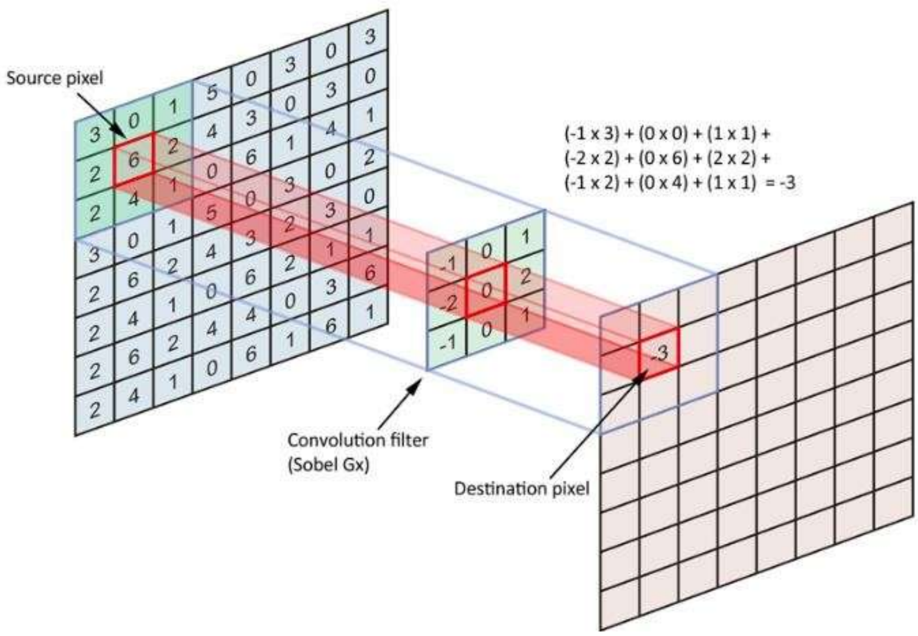
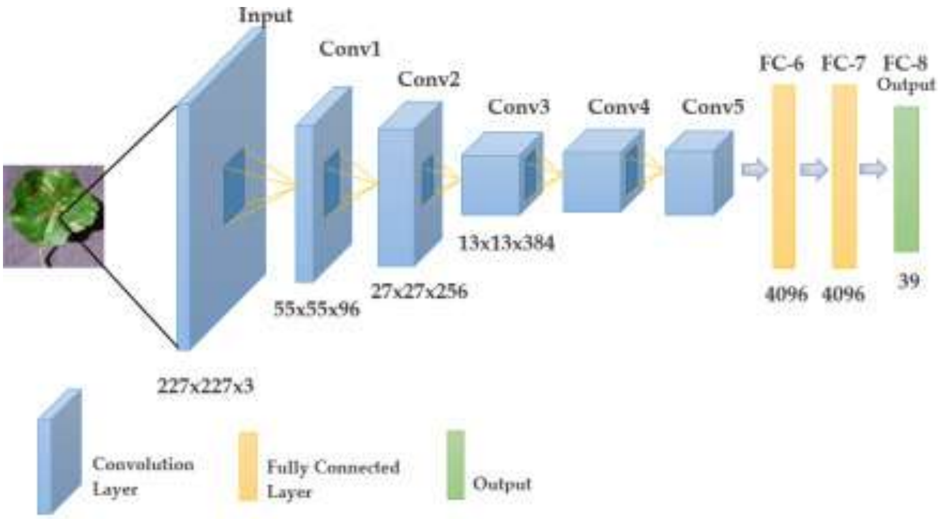


Figure 2: The filter slides over the input and performs its output on the new layer

3.2 State of the art CNN based models

The discussion of the various networks is presented in the next sections:



AlexNet

The AlexNet model is an 8-layer CNN architecture and the architecture follows the design of LeNet-5 (LeCun et al., 1989). This architecture uses ReLU activation function in the convolutional and fully connected layers. It has approximately 61 million parameters (Krizhevsky et al., 2012). The AlexNet architecture takes the input image size as 227 × 227. It is consists of five convolutional layers followed by three fully connected layers and finally the Softmax layer (see given in Fig. 2. 2) . The fully connected layer FC-8 of AlexNet architecture used in this study is connected to the Softmax layer with 39 neurons. Each output value in the Softmax layer is the ratio of the input image to the class represented by the corresponding output. The aim of Softmax layer is to generate a distribution using the inputs coming from the FC-8 layer and assigns a probability value for each class which of total is 1 for all classes.

Figure 3: Schematic representation of AlexNet.

VGG16

VGG16 is a CNN architecture that contains 16 layers and the input layer takes images of 224 × 224 pixels. It has approximately 138 million parameters and instead of having large number of hyper-parameters, it always has the same convolution layers that use 3 × 3 filters with stride 1 and same padding and maximum pooling layers that use 2 × 2 filters with stride 2 (Simonyan and Zisserman, 2014). The VGG16 architecture follows this convolution and maximum pooling layers arrangement consistently throughout the entire architecture (see Fig. 2.3). Finally, there are 3 FC layers first two with ReLU and the last with Softmax activation function.

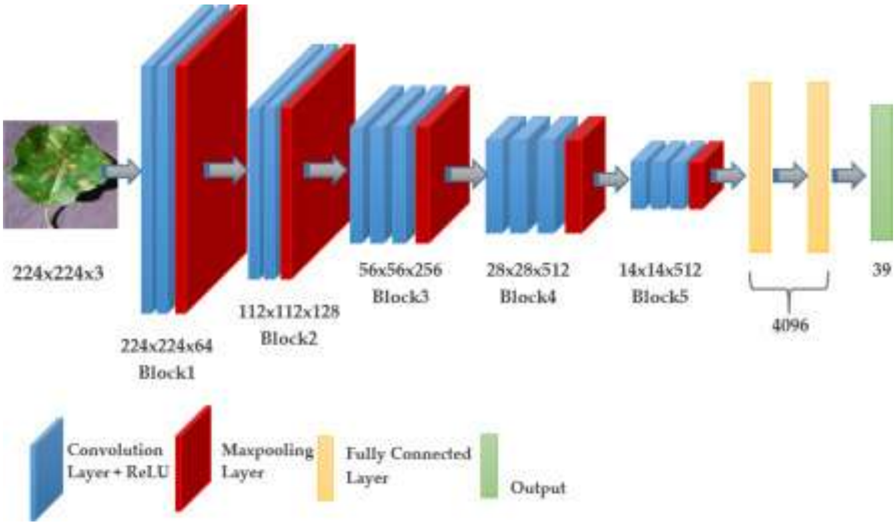


Figure 4: Schematic representation of VGG16.

ResNet50

ResNet50 architecture (He et al., 2016), which won the ILSVRC-2015 competition in 2015, is an architecture proposed to solve the problem of multiple non-linear layers not learning identity maps and degradation problem. ResNet50 is a network in network architecture based on many stacked residual units (Fig. 4). Residual units are used as building blocks to build the network. These units consist of convolution and pooling layers. This architecture uses 3 × 3 filters as VGG16 and takes input images of 224 × 224 pixels.

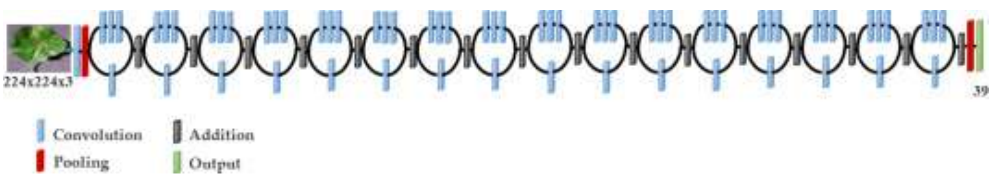


Fig. 4. Schematic representation of ResNet50.

Inception V3

Inception V3 (Szegedy et al., 2016) developed by Google, is the third release in the Deep Learning Evolutionary Architectures series. After the Inception V1 architecture was developed by Szegedy, batch normalization was performed in Inception V2. Then the idea of factorization was introduced in

Inception V3. The main purpose in factorization is to reduce the number of connections and parameters without reducing the efficiency of the network. The model itself consists of symmetrical and asymmetrical building blocks containing convolutions, average pooling, max pooling, concats, dropouts and fully connected layers (Fig. 5). The Inception V3 architecture, which has the Softmax function in the last layer, consists of 42 layers in total and the input layer takes images of 299 × 299 pixels.

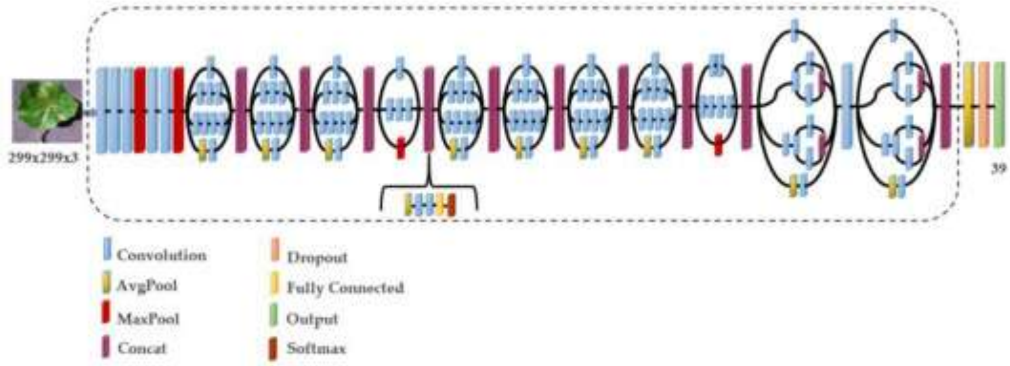


Figure 5: Schematic representation of Inception V3.

EfficientNet

Success has increased as the models used in the ImageNet dataset since 2012 have become more complex, but many are not effective in terms of computing load. EfficientNet model, which is among the state-of-the-art models by reaching 84.4% accuracy with 66 M parameter in the ImageNet classification problem, can be considered as a group of CNN models. EfficientNet group consists of 8 models between B0 and B7, and as the model number grows, the number of calculated parameters does not increase much, while accuracy increases noticeably. Unlike other CNN models, EfficientNet uses a new activation function called Swish instead of the Rectifier Linear Unit (ReLU) activation function (Tan and Le, 2019).

The aim of deep learning architectures is to reveal more efficient approaches with smaller models. EfficientNet, unlike other state-of-the-art models, achieves more efficient results by uniformly scaling depth, width, and resolution while scaling down the model. The first step in the compound scaling method is to search for a grid to find the relationship between the different scaling dimensions of the baseline network under a fixed resource constraint. In this way, a suitable scaling factor for depth, width and resolution dimensions is determined. These coefficients are then applied to scale the baseline network to the desired target network (Tan and Le, 2019).

The main building block for EfficientNet is the inverted bottleneck MBConv, which was first introduced in MobileNetV2 (Mark et al., 2018), but due to the increased FLOPS (floating point operations per second) budget, it is used slightly more than MobileNetV2. In MBConv, blocks consist of a layer that first expands and then compresses the channels, so direct connections are used between bottlenecks that connect much fewer channels than expansion layers. This architecture has in-depth separable convolutions that reduce calculation by almost k2 factor compared to traditional layers where k is the kernel size which denotes the width and height of the 2D convolution window (Mark et al., 2018). The schematic representation of EfficientNet B0 model is shown in Figure 6.

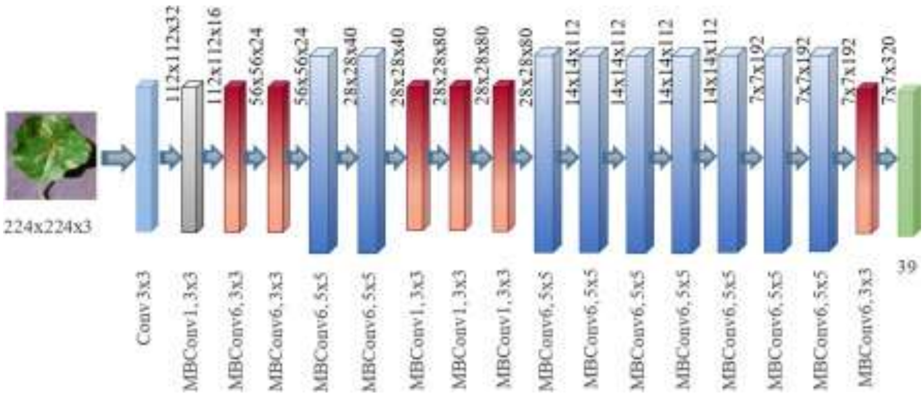


Figure 6: Schematic representation of EfficientNet

3.3 Importance of rice as a crop and diseases of rice

As a cereal grain, rice is the most widely consumed staple food for over half of the world's human population (Nguyen, 2020). Rice is the main crops in Bangladesh. Like many other developing countries rice is the major source of income for the rural people/farmers especially in Bangladesh. Therefore, when rice production is hindered due to rice disease, it impacts on the national economy. For example, Blast disease of rice causing 11-15% yield loss annually (Hossain, Ali, & Hossain 2017). Sarker et al. (2016) reported that Sheath blight (a rice disease caused by Rhizoctonia solani) affects the crop in almost every season in Bangladesh. The disease reduces quality as well as quantity of the crops which in turn affects the economy of the country like Bangladesh where agriculture is the main occupation.

Rice disease is an abnormal physiological process that distorts the rice plant's normal structure, growth and function. Among the diseases, Brown Spot (Helminthosporium oryzae), Sheath Rot (Sarocladium oryzae), Sheath Blight (Rhizoctonia Solani), False Smut (Ustilaginoidea virens), Grain discolouration (fungal complex), and Leaf streak (Xanthomonas oryzae pv. Oryzicola) are common rice diseases in Bangladesh. Below we present symptoms of the diseases (table1):

Table 1.1: Various rice disease and infected leaves

Disease	Symptom	Image of diseased leaf	Reference
Rice false smut	Leaves are transformed into yellow or greenish velvety spore balls.		Nessa et al. (2018)
Sheath Blight	On the leaf sheath oval or elliptical or irregular greenish gray spots are formed. As the spots enlarge, the centre becomes greyish white with an irregular blackish brown or purple brown border.		Parveen, Hossain, & Ali (2018)
Blast disease of rice	Blast can occur wherever blast spores are present. The blast is the gray colored spot.		Hossain, Ali & Hossain, (2017); Khan et al. (2016).
Ufra	Ufra disease on deepwater rice, Bangladesh; note partial emergence and distorted panicles due to nematode infection.		Khanam et al. (2016)
Calcium deficiency of rice	tips of youngest leaves become white or bleached, rolled, and curled. Old leaves eventually turn brown		Naila et al. (2019). .

3.4 Rice disease detection using digital image processing technologies

The literature review suggests that four approaches are used for the automatic diagnosis of rice diseases.

. The first approach for automatic rice disease detection is conventional means such as pattern recognition techniques (Phadikar & Sil, 2008; Rahman et al., 2020). Following this approach, Phadikar & Sil (2008) proposed a rice disease identification approach where the diseased rice images were classified utilizing Self Organizing Map (SOM) (via neural network) in which the train images were obtained by extracting the features of the infected parts of the leave while four different types of images were applied for testing purposes. A somewhat satisfactory classification results were reported. Islam et al (2018) study presents a new technique using only one feature i.e. RGB values to detect and classify the diseases based. The disease is based on percentage of RGB value of the affected portion using image processing. Once the percentage of RGB from the affected region is extracted and grouped into various classes, they are fed to a simple classifier called Naive Bayes which classifies the disease into various categories. This technique has successfully detected and identified three rice diseases, namely rice, brown spot, rice bacterial blight, and rice blast. This technique is efficient and faster because it uses only one feature i.e. RGB values of the affected portion which requires minimum computation time to identify and classify the diseases. Rather than processing the whole leaf, this technique even successfully detects the diseases using only a small sample of a leaf containing the affected portion of rice disease.

The second method is using support vector machine. For example, Phadikar, Sil & Das, 2012; Prajapati, Shah & Dabhi, 2017 utilized this method. Phadikar, Sil & Das (2012) proposed an automated approach to classify the rice plant diseases, namely leaf brown spot and the leaf blast diseases based on the morphological changes. A total of 1,000 spot images captured by Nikon COOLPIX P4 digital camera from a rice field were used. The results obtained were 79.5% and 68.1% accuracies from the Bayes' and SVM classifiers, respectively. Support Vector Machine (SVM) technique was also utilized by Prajapati, Shah & Dabhi (2017) for multi-class classification to identify three types of rice diseases (bacterial leaf blight, brown spot, and leaf smut). The images of infected rice plants were captured using a digital camera from a rice field and obtained 93.33% accuracy on training dataset and 73.33% accuracy on the test dataset.

Thirdly, digital image processing techniques by Arnal Barbedo, 2013; Zhou et al., 2013; Sanyal et al., 2008; Sanyal & Patel, 2008 Study. For example, Zhou et al. (2013) investigated a technique to evaluate the degree of hopper infestation in rice crops where a fuzzy C-means algorithm was used to classify the regions into one of four classes: no infestation, mild infestation, moderate infestation and severe infestation. Their study illustrated that the accuracy reached 87% to differentiate cases in which rice plant-hopper infestation had occurred or not whilst the accuracy to differentiate four groups was 63.5 %. Sanyal et al. (2008) proposed an approach for detecting and classifying six types of mineral deficiencies in rice crops where each kind of feature (texture and color) was submitted to its own specific multi-layer perceptron (MLP) based neural network. Both networks consist of one hidden layer with a different number (40 for texture and 70 for color) of neurons in the hidden layer where 88.56% of the pixels were correctly classified. Similarly, the same authors proposed another similar work (Sanyal & Patel, 2008) where two kinds of diseases (blast and brown spots) that affect rice crops were successfully identified.

The fourth approach is the texture analysis and feature extraction using computer vision for enhancing the accuracy and rapidity of diagnosing the results. Asfarian et al. (2014) developed a new approach of texture analysis to identify four rice diseases (bacterial leaf blight, blast, brown spot and tungro virus) using fractal Fourier. In their proposed study, the image of the rice leaf was converted to CIELab color space and the system was able to achieve an of accuracy 92.5%. The feature extraction from diseased and unaffected leaf images, the gray level co-occurrence matrix (GLCM) and the color moment of the leaf lesion region were implemented by Ghyar & Birajdar (2018) to create a 21-D feature vector and related features. The redundant features were eliminated with the genetic algorithm-based feature selection method to generate 14-D feature vectors to minimize complexity. The technique has shown a promising result; however, to improve its detection accuracy there is need for more optimization procedure to take place. The rice disease from the brown spot and blast diseases was described utilizing the color texture of rice leaf photos by Sanyal & Patel (2008). However, the technological standard of identification of rice diseases needs to be strengthened.

In Phadikar & Sil (2008), the entropy-based bipolar threshold technique was employed for segmentation of the image after improving its brightness and contrast. The author sought to integrate the image processing and soft computing technique for the detection of rice plant attacked by several types of diseases. The idea behind the technique was robust when utilized effectively. However, the average accuracy of identification on the four datasets was 82 percent which indicates that more enhancement is still required. The image processing and machine learning methods were utilized to non-destructively screen seedlings with rickets by Chung et al. (2016). Moreover, genetic algorithms were employed to develop SVM classifiers in order to optimize feature selection and model parameters for differentiating healthy seedlings and infected ones. The overall accuracy achieved in their study was 87.9 percent. However, since various diseases may have several symptoms, this approach should be tested if it is needed to use in other diseases, suggesting that this procedure has some limitations.

The final approach is moving towards deep learning models in an effort to detect diseases in various plants The Convolutional Neural Networks (CNN) is a deep learning method that has become one of the best image classification technique which has already acquired great success (Xu et al., 2017; Zhao & Jia, 2016; Sainath et al., 2015; Ribeiro et al., 2016; Ciresan et al., 2011; Kawasaki et al., 2015).

Chen et al. performed the detection of rice plant disease with a deep neural network of Convolutional Neural Network (CNN) (Chen et al., 2020c). Using CNN's VGGNet architecture, Chen et al. performed maize plant and rice plant disease classification (Chen et al., 2020d). . Chen et al. also proposed a new model namely MobileNet-Beta by expanding the pre-trained MobileNetV2 model for the detection of plant diseases called (Chen et al., 2020b). Too et al., reported that the DenseNet architecture of CNN the highest test accuracy with 99.75% (Too et al., 2019). Geetharamani and Pandian trained the 9-layer CNN architecture in the PlantVillage dataset and the model achieved 96.46% classification accuracy on the test dataset (Geetharamani and Pandian, 2019). Mohanty et al. (2016), on the other hand used AlexNet and GoogLeNet of CNN to classify classified plant diseases and obtained 99.35% classification accuracy (Mohanty et al., 2016). Using PlantVillage, Ferentinos's model of VGG architecture provided highest accuracy with 99.53% (Ferentinos, 2018).

Lu et al. (2017b) study has experimented the automatic identification and diagnosis of rice diseases using CNN as deep learning method. Using a dataset of 500 natural images of diseased and healthy rice leaves and stems captured from rice experimental field, CNNs are trained to identify 10 common rice diseases. Under the 10-fold cross-validation strategy, the proposed CNNs-based model achieves an accuracy of 95.48%.

Zhou et al. (2019) suggested Faster R-CNN approach, which seems to be ideal for the detection of rice diseases due to its good speed and high accuracy. Shrivastava et al. (2019) also applied CNN, for rice plant disease classification using transfer learning of deep convolution neural network. Using AlexNet CNN model, the model is able to classify rice diseases with classification accuracy of 91.37%.

Another method suggested by Ren et al. (2017) was capable of detecting plant diseases as well as enhancing the accuracy using Faster R-CNN. However, it is required to reduce the time for disease identification in order to allow it to be suitable for monitoring large-scale cultivation.

In a recent study, Rahman et al. (2020) developed a CNN approach for detecting diseases and pests (five classes of diseases, three classes of pests and one class of healthy plant and others) from rice plant images. A total number of 1,426 images were collected that were captured using four different types of cameras and the system achieved a mean validation accuracy of 94.33 %.

Rahman et al. (2020) suggested a new stacked CNN architecture which uses two-stage training to substantially reduce the model size while retaining high classification accuracy. The CNN architectures such as MobileNet, NasNet Mobile and SqueezeNet. Experimental results show that the proposed architecture can achieve the desired accuracy of 93.3% with a significantly reduced model size (e.g., 99% smaller than VGG16).

3.5 Knowledge gap in rice leaf detection using image processing

Though, the methods for automatic rice disease diagnosis based on digital images processing have received special attention, earlier, Islam (2018) identified Rice leaf disease detection using deep learning method is under researched. Bari et al. (2021) has criticized for low accuracy rate of rice disease detection models. Our literature review supports Bari et al. (2021), as most methods in this literature review reported classification accuracies between 50% and 95%. Those achieving higher accuracies were usually tested with fewer diseases and, in most cases, only one plant species. Those methods may not hold such a good performance when more diseases are added or other plant species are considered. More considerations about this problem can be found in Barbedo (2016).

Despite the fact there are several architectures available in CNN, most studies utilized one network rather comparing the accuracy using several architecture. Our this findings also supports Atila et al. (2021) that advocates novel deep learning architectures in rice leaf disease detection is yet to be implemented. Earlier, Barbedo (2016) also complained that there is a lack of methods that can be used under the real, uncontrolled conditions found in the field. Moreover, the gap between the current capabilities of image-based methods for automatic rice disease identification and the real-world needs is still wide (Barbedo, Koenigkan & Santos 2016).

4. Research methodology

This research aims to detect rice disease on leaf using deep neural network of CNN. The experiment was conducted using python. Here, we present our process of work for the detection of diseases in rice plants. In this research the main aim is improving the accuracy of rice disease classification. As our images in the dataset are pre-processed, we would not dive deep into the image pre-processing and segmentation steps. In the next section we discuss about the dataset utilized in this research.

4.1 Dataset

In this study, we use the “Rice Leaf Disease Dataset” from the UCI Machine Learning Repository available at https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases. The dataset contains the rice plant leaf images with only the three types of diseases we need to deal with, 40 images for disease class. Images in the dataset are colored images of varying sizes. The dataset has white background images. The training and test datasets are in the ratio of 70:30 of the original dataset (see table 2).

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Table 2. Division of images into train, test and validation sets

	Data	Testing	Validation
Original Dataset	120	84	36
Augmented Dataset	34,980	24,486	3498

4.2 Process of work

First step: Image Acquisition

In this step we downloaded the images from the site https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases to provide as input

Second step: Image augmentation

An image augmentation function is used in this step. Image augmentation is the procedure by which an existing dataset is expanded by transforming the original dataset in order to create new data, and in such a way that the new data are label preserving (Bloice et. al. 2019).. The goal is to increase the variance of the dataset, while ensuring that new data are meaningful and does not merely add unnecessary volume to the dataset (Bloice et. al. 2019). When used in a machine learning context, it can improve model generalization, make trained models more robust to unseen data, and increase model accuracy. (Bloice et. al. 2019). With the aims, we propose data augmentation in the training data. At each iteration, we will take one augmentation technique and will apply that on the samples

- Horizontal flipping.
- Rotation of the image (between −22 to 22°).
- Changing the brightness (1.2 to 1.5 times the original brightness).
- Scale to 80–120% of image height/width (each axis independently).
- Translate by −20 to +20 relative to height/width (per axis).
- Shear the image by −16 to +16°.

Third step: Training

A CNN learner model is created at this stage. Using of the DenseNet, EfficientNetB3, MobileNet, VGG16 and ResNet10 architecture, a model is created to train the model on the given dataset and then tested to measure the accuracy. Features such as top_losses, most_confused, etc. are observed in order tointerpret the results of the model.

Forth step: Classifier

In this step, neural networks are used in the automatic detection of leaf diseases. The neural network is chosen as a classification tool due to its well known technique as a successful classifier for many real applications. After the training model, the evaluation model is build that detect rice disease based on the highest probability of occurrence, the images of leaves are classified into disease classes using the Softmax layer.

5. Results and discussions

In this section, the performance of rice leaf disease detection of CNN using DenseNet, EfficientNetB3, MobileNet, VGG16 and ResNet10 architecture are presented. First we place the accuracy of the models, then we discuss the overall measures for the models, gathering in addition to the descriptors, possible causes, and areas of opportunity for improvement of results.

The performance of the CNN networks are realized and compared between models through quality measures. The quality measures are based on accuracy, precision and recall.

Accuracy is one metric for evaluating classification models. Informally, accuracy is the fraction of predictions our model got right. Formally, accuracy has the following definition: Accuracy = Number of correct predictions Total number of predictions. Accuracy is the ratio of correctly labeled images to the total number of samples (Gonzalez-Huitron et al.2021).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Here TP refers to true positives, TN to true negatives, FP to false positives and FN to false negatives. Also training times and confusion matrices are presented for the four models implemented in this work. Following table (Table 3) shown the values of TP, TN, FP and FN of the experimented architectures of CNN.

Table 3: TP, TN, FP and FN of the experimented architectures of CNN

	EfficientNetB3			
	TP	FP	TN	FN
Bacterial leaf blight	9	3	21	3
Brown spot	3	9	24	0
Leaf smut	12	0	18	9
	DensNet121			
Bacterial leaf blight	12	0	24	0
Brown spot	11	1	24	0
Leaf smut	12	0	23	1
	MobileNet			
Bacterial leaf blight	12	0	22	2

Brown spot	11	1	23	1
Leaf smut	9	3	23	1
VGG16				
Bacterial leaf blight	12	0	24	0
Brown spot	10	2	23	1
Leaf smut	11	1	22	2
ResNet10				
Bacterial leaf blight	12	0	23	1
Brown spot	10	2	24	0
Leaf smut	12	0	23	1

Table 4 shows the accuracies obtained in the test sets of DenseNet, EfficientNetB3, MobileNet, VGG16 and ResNet10 models. Test accuracy given in these figures was calculated as the ratio of number of correctly classified samples to number of all samples. The DenseNet model achieved the highest accuracy with 99.22% and EfficientNetB3 gave the lowest accuracy values with 80.47%. The performance of the DenseNet suggest that in the case of 1000 rice leaf disease diagnosis, the model accurately detected result 992.2 times.

Table 4: Accuracy of CNN networks in detecting rice disease

	Accuracy	Loss
DenseNet121	99.22%	0.26%
MobileNet	97.66%	0.76%
VGG16	97.66%	2.16%
ResNet10	95.31%	0.87%
EfficientNetB3	80.47%	5.84%

Precision is the probability given a positive label, how many of them are actually positive (Gonzalez-Huitron et al. 2021). Precision tells us how many of the correctly predicted cases actually turned out to be positive. Precision is a useful metric in cases where False Positive is a higher concern than False Negatives.

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

Recall or Sensitivity is the accuracy of positive predicted instances describing how many were labeled correctly (Gonzalez-Huitron et al. 2021).Recall tells us how many of the actual positive cases we were able to predict correctly with our model. Recall is a useful metric in cases where False Negative trumps False Positive.

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

F1 score, as an additional measure of classifier accuracy, which considers both precision and recall. F1-score is a harmonic mean of Precision and Recall, and so it gives a combined idea about these two metrics. It is maximum when Precision is equal to Recall.

But there is a catch here. The interpretability of the F1-score is poor. This means that we don’t know what our classifier is maximizing – precision or recall? So, we use it in combination with other evaluation metrics which gives us a complete picture of the result.

$$F1 - score = \frac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$$

Table 5: Precision, Recall, f1 and Specificity

	EfficientNetB3			
	Precision	Recall	f1	Specificity
Bacterial leaf blight	0.75	0.75	2.8	0.87
Brown spot	0.25	1	6	0.72

Leaf smut	1	0.57	2.14	1
DensNet121				
Bacterial leaf blight	1	1	3	1
Brown spot	0.91	1	3.09	0.96
Leaf smut	1	0.92	2.84	1
MobileNet				
Bacterial leaf blight	1	0.85	2.71	1
Brown spot	0.91	0.91	2.92	0.95
Leaf smut	0.75	0.9	3.13	0.88
VGG16				
Bacterial leaf blight	1	1	3	1
Brown spot	0.83	0.90	3.01	0.92
Leaf smut	0.91	0.84	2.78	0.95
ResNet10				
Bacterial leaf blight	1	0.92	2.84	1
Brown spot	0.83	1	3.24	0.92
Leaf smut	1	0.92	2.84	1

The Precision, Recall, f1 and Specificity obtained for of DenseNet, EficientNetB3, MobileNet, VGG16 and ResNet10 models for each of the class (table 5). Considering the precision values for each on the test dataset, DenseNet architecture provides the best performance. The above table suggest that DenseNet model classified Bacterial leaf blight and leaf smut 100% positive. however Brown spot was classified 91 times positively within 100 times. Moreover, in DenseNet recall in the class of Leaf Smut is 0.92, this implies the model 92% correctly identifies of all the leaf smut.

Specificity value of the class Bacterial leaf blight and Leaf smut is 100%, mans that both of the diseases were correctly detected every time. Brown spot detection was 96%, mans that 4 of every 100 detections are miss-labeled as brown spot and 96 are correctly labeled as brown spot.

6. Conclusion and future research direction

Plant disease detection through leaf image processing utilizing deep learning methods have recently become popular. Among deep learning methods, CNN has attacked significant attention for image processing and pattern recognition (Gonzalez-Huitron et. al. 2021; Karthik et al 2020; Sharma et al. 2020). In this research the accuracy of DenseNet architecture of CNN was found highest in classifying rice disease. The success of the proposed architecture was compared with the state-of-the-art CNN architectures such as DenseNet, EfficientNetB3, MobileNet, VGG16 and ResNet10. Experimental studies were conducted in both original and augmented versions of the image dataset. Considering both the average accuracy and the average precision metric on both the original and augmented datasets, the DenseNet models were found to be superior to other CNN architectures. The DenseNet model achieved 99.22% accuracy and 98.42% precision in the original dataset. Furthermore, the DensNet121 architecture provides superior result in recall and f1 value than other CNN models considered in this research.

However, there are a number of limitations at the current stage of the research, those need to address in future work. First, one can complain that the research has considered three classes or diseases of rice. In defense we can say we managed the dataset of three classes. In future, we have plan to increase disease class through other dataset. in this research data were collected available online, however, future research should consider collecting rice leaf from field. Collection of leaves from field will provide a diverse dataset. A more diverse set of training data is needed to improve the accuracy. Moreover, as the mobile technologies are improving and more mobiles are in the hand of farmers, offering such a system with a simple mobile application should help farmers (Ferentinos, 2018). One important limitation in this research is the experiments conducted using the CNN architecture considered to the classification of single leaves, facing up, on a white background. While these are straightforward conditions, a real world application should be able to classify images of a disease as it presents itself directly on the plant. Indeed, many diseases don't present themselves on the upper side of leaves only (or at all), but on many different parts of the plant. Thus, new image collection efforts should try to obtain images from many different perspectives, and ideally from settings that are as realistic as possible.

6.1 Expected contribution of the research

This research offers several critical contributions. Some contributions are applied that can bring benefits to the Bangladeshi government and agriculture related stakeholders. The research focused deep learning method for disease detection in one of the under research herd crop: Rice which is the main food in many countries. Moreover, Rice leaf disease detection using CNN is under researched (Islam 2018). Moreover, the latest computer-based rice leaf disease detection is yet to be improved due to low accuracy rate in models (Bari et al. 2021). Despite the fact there are several architectures available in CNN, most studies utilized one network rather comparing the accuracy using several architecture. There are gaps to be investigated regarding the use of especially new deep learning architectures in rice leaf disease detection (Atila et al. 2021).

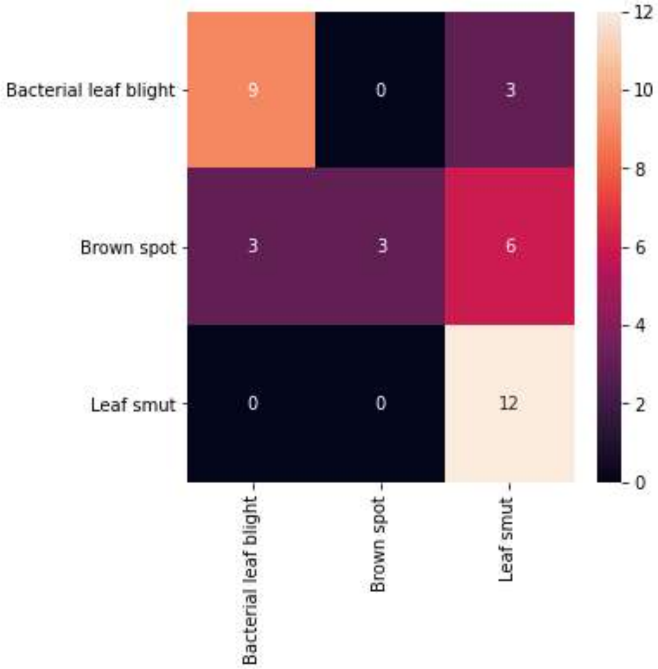
Bangladeshi government is attempting to digitalize the country by including computing in possible every sector in the country. The Bangladesh government has targeted Sustainable development goals (SDG) by 2030 and this research is expected to offer substantial practical implications for Government of Bangladesh and the agriculture ministry. Bangladesh is important rice producing country in the world, hence Bangladesh is probably one of the countries with the greatest need for research attention in the computer based disease detection of the plants.

7. Declaration of Competing Interest

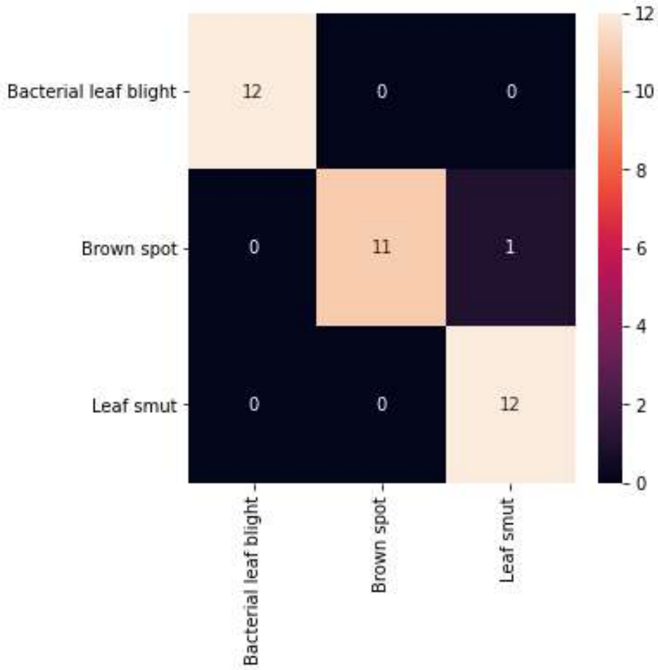
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Confusion matrix of CNN networks

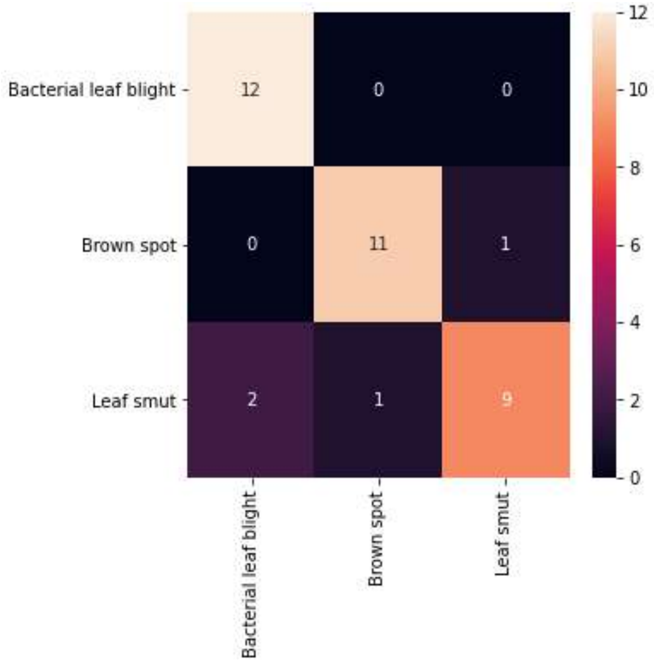
EfficientNetB3



DensNet121

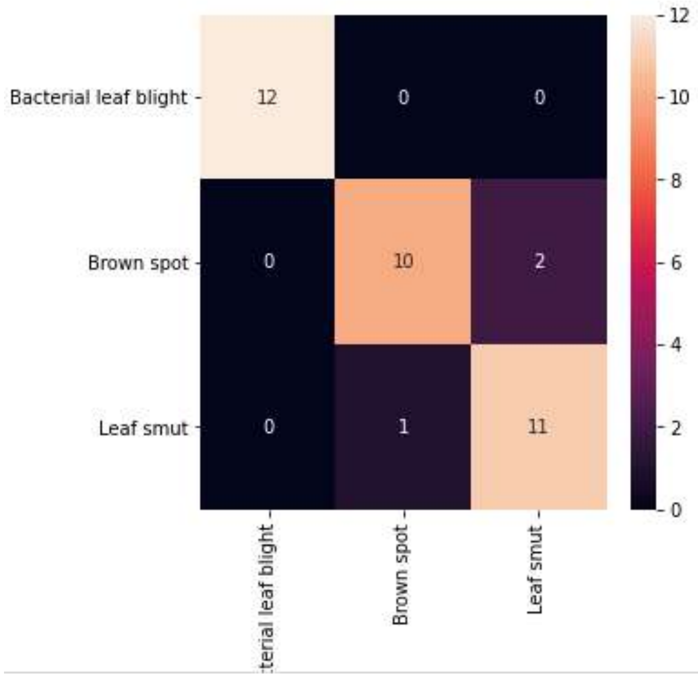


MobileNet



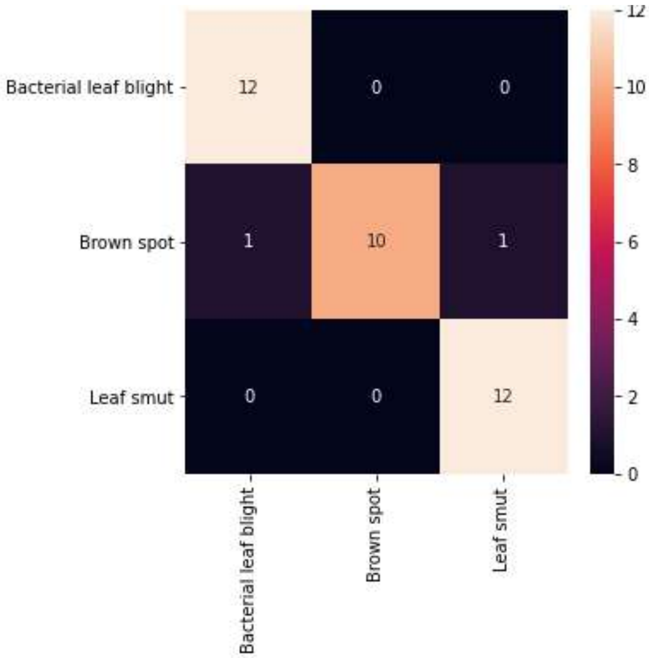
Bacterial leaf blight
Brown spot
Leaf smut
12
0
0
0
11
1
2
1
9
Bacterial leaf blight
Brown spot
Leaf smut
12
10
8
6
4
2
0

VGG16



Bacterial leaf blight
Brown spot
Leaf smut
12
0
0
0
10
2
0
1
11
Brown spot
Leaf smut
12
10
8
6
4
2
0

ResNet10



Bacterial leaf blight
Brown spot
Leaf smut
12
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0
12
Bacterial leaf blight
Brown spot
Leaf smut
12
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CONCLUSION

Plant disease detection through leaf image processing utilizing deep learning methods have recently become popular. Among deep learning methods, CNN has attacked significant attention for image processing and pattern recognition (Gonzalez-Huitron et. al. 2021; Karthik et al 2020; Sharma et al. 2020). In this research the accuracy of DenseNet architecture of CNN was found highest in classifying rice disease. Whereas most CNN studies focused experimenting a single network on a given plant disease detection, this study focused the success of the most suitable network in detecting rice leaf disease. The success of the DenseNet architecture was compared with the state-of-the-art CNN architectures such as DenseNet, EfficientNetB3, MobileNet, VGG16 and ResNet10. Experimental studies were conducted in both original and augmented versions of the image dataset. Considering both the average accuracy and the average precision metric on both the original and augmented datasets, the DenseNet models were found to be superior to other CNN architectures. The DenseNet model achieved 99.22% accuracy and 98.42% precision in the original dataset. Furthermore, the DensNet121 architecture provides superior result in recall and f1 value than other CNN models considered in this research.

However, there are a number of limitations at the current stage of the research, those need to address in future work. First, one can complain that the research has considered three classes or diseases of rice. In defence, we can say we managed the dataset of three classes. In future, we have plan to increase disease class through other dataset. In this research data were collected available online, however, future research should consider collecting rice leaf from field. Collection of leaves from field will provide a diverse dataset. A more diverse set of training data is needed to improve the accuracy. Moreover, as the mobile technologies are improving and more mobiles are in the hand of farmers, offering such a system with a simple mobile application should help farmers (Ferentinos, 2018). One important limitation in this research is the experiments conducted using the CNN architecture considered to the classification of single leaves, facing up, on a white background. While these are straightforward conditions, a real world application should be able to classify images of a disease as it presents itself directly on the plant. Indeed, many diseases don't present themselves on the upper side of leaves only (or at all), but on many different parts of the plant. Thus, new image collection efforts should try to obtain images from many different perspectives, and ideally from settings that are as realistic as possible.

Expected contribution of the research

This research offers several critical contributions. Some contributions are applied that can bring benefits to the Bangladeshi government and agriculture related stakeholders. The research focused deep learning method for disease detection in one of the under research herd crop: Rice which is the main food in many countries. Moreover, Rice leaf disease detection using CNN is under researched (Islam 2018). Moreover, the latest computer-based rice leaf disease detection is yet to be improved due to low accuracy rate in models (Bari et al. 2021). Despite the fact there are several architectures available in CNN, most studies utilized one network rather comparing the accuracy using several architecture. There are gaps to be investigated regarding the use of especially new deep learning architectures in rice leaf disease detection (Atila et al. 2021).

Bangladeshi government is attempting to digitalize the country by including computing in possible every sector in the country. The Bangladesh government has targeted Sustainable development goals (SDG) by 2030 and this research is expected to offer substantial practical implications for Government of Bangladesh and the agriculture ministry. Bangladesh is important rice producing country in the world, hence Bangladesh is probably one of the countries with the greatest need for research attention in the computer based disease detection of the plants.

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