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Application of deep learning for rice leaf disease detection in the Mekong Delta

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ABSTRACT

The Mekong River Delta, the largest rice-producing region in Vietnam with an annual output of over 25 million tons, plays a vital role in ensuring food security both within the country and globally. In recent years, it has undergone significant transformation in rice cultivation, which aims to support farmers here to plant rice more effectively. However, severe weather conditions and soil degradation have negatively impacted rice growth. Additionally, rice is highly susceptible to various diseases that must be identified and prevented promptly. As a result, leveraging technology such as AI and deep learning to diagnose rice diseases based on leaf symptoms is essential. This paper utilizes an image dataset of three common rice leaf diseases—leaf smut, brown spot, and bacterial leaf blight—and applies deep learning networks (MobileNet and ResNet) to evaluate and select the best model. A diagnostic program is then developed to detect these diseases. Experimental results show that the MobileNetV3-Small model (a variant of the MobileNet network) is the most optimal, offering fast training time, high accuracy, and acceptable levels of loss and error.

1. INTRODUCTION

In recent years, Information Technology (IT) has dramatically developed in which it primarily focuses on core technologies of the Industrial Revolution 4.0 such as artificial intelligence (AI), Internet of T (IoT), block chain and virtual reality (VR), etc. Particularly, AI has become an inevitable growing trend in modern society, a decision to the success or failure of enterprises and a major factor to direct the enterprise's growth in supplying products and services to customers. On the macro-scale, AI significantly contributes to the socio-economic growth and impulsion which can solve tough questions in key areas such as military, health, agriculture, forest management and education. Thus, in the current rice production and cultivation area, Vietnam has been applying achievements of the Industrial Revolution into the production process to enhance the rice's quality and productivity even in disadvantageous conditions, contributing to creating beneficial, professional and easy working environment for farmers.

One of the biggest problems encountered e by Vietnamese farmers in farming and producing process is how to prevent rice diseases efficiently. Henceforth, diseases can be timely prevented and treated to maintain crop quality and productivity. More particularly, leaf smut, brown spot and bacterial leaf blight are three common diseases in the rice growing process in every new crop (Figure 1) (Minh, 2014, 2020). The symptoms on rice leaves caused by the three mentioned diseases are quite similar, making them difficult to distinguish immediately. Moreover, the rapid and widespread speed of these diseases severely impacts the productivity of rice crops. In addition to instructional methods of agricultural experts such as three reductions, three increases (reduce volume of rice seeds, reduce fertilizers, reduce pesticides, increase productivity, increase quality and increase effectiveness), clean rice fields, transfer plants among crops, etc., searching for solutions to detect early diseases in replacement of self-comparison to images, documents and of experience to diagnose needs to be more concerned in constant technology development.

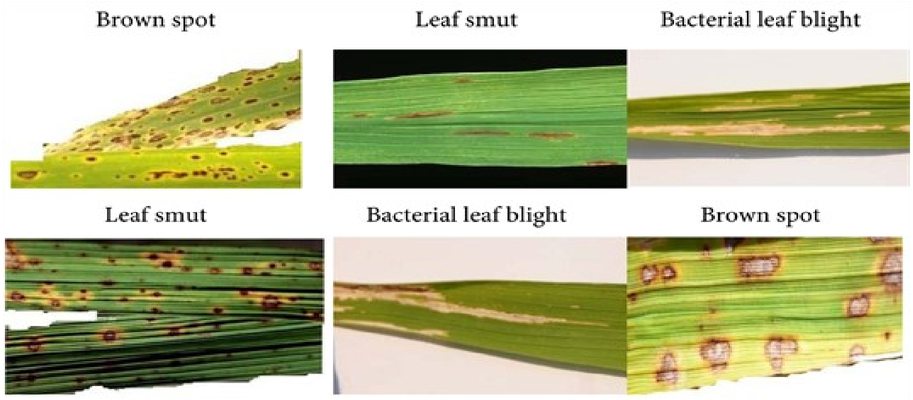

Figure 1. Features of leaf smut, brown spot, bacterial leaf blight on rice leaves

Today, AI is one of the most important technological sectors, helping humans solve numerous challenges and gaining global attention for its innovative and advanced features (Pham et al., 2022). In which, deep learning technique is a subset of machine learning which has become one of the primary breakthroughs of AI. It is widely applied in various fields in our country, even in agriculture sector with many outstanding achievements in order to serve and support farmers in the production process.

This study uses the database of three common and distinct diseases on rice leaves including leaf smut, brown spot and bacterial leaf blight, and deep learning techniques with models of MobileNet, ResNet to evaluate and select the best model. Then, a diagnostic program was built based on that model. The experimental findings show that eNetV3-Small model (the representative of MobileNet model) is the most optimal model with short training time, high accuracy, acceptable model's loss and errors. A program is successfully built to detect the above-mentioned diseases in a fast and accurate way. This program efficiently supports and creates the best conditions for farmers in rice production and cultivation.

2. RELATED WORK

2.1. Overview of ResNet model and building ResNet50 model

ResNet (Residual Networks) is a CNN network (Convolutional Neural Network) designed to work with thousands of layers. Since its first launch in 2015, it has received the public concern. It even gained the first rank on ILSVRC in 2015 with only *3.57% top-5 error* rate. It also won the first place in ILSVRC and COCO in 2015 with challenges in computer vision field. Since then, Modeling network has become popular in this field. Thanks to its strong performance, efficiency in machine vision and image classification applications is boosted. Some typical examples are object detection and facial recognition. ResNet resembles of other networks including convolutional layers (to extract features from input images or other input data using filters or kernels), pooling (to reduce space size of typical output maps from layers), activation (applied after weight layers to introduce non-linearities into the model) and fully connected layer (an artificial neural layer in which each neuron in this layer is connected to neurons previous layer via specific weights).

Series of variants of this architecture were introduced after ResNet. The experiment shows that these architectures could train neural networks with a depth of millions of layers and rapidly became the most popular architecture in computer vision. ResNet50, a ResNet architecture's variants, is one of the most popular and efficient convolutional neural network models which proves its remarkable capacity in facial recognition tasks and medium-size image classification in comparison to larger ResNets: ResNet101 or ResNet152 (only 50 layers compared to 101 and 152 layers). It helps to save calculating resources and storage during the training process and implementation in an easy way.

Moreover, ResNet50, apart from being used to classify images, is also used to extract features from the images. This makes it useful in various applications such as object detection, image classification and image classification in medicine (He et al., 2016). For those reasons, ResNet50 is chosen to be the typical network model representing ResNet to conduct the evaluation program to select the best classification model.

2.2. Overview of MobileNet deep learning model and building MobileNetV3

MobileNet is a convolutional neural network developed by a team of researchers at Google. This architecture not only performs high accuracy results but also allows to keep the lowest parameters and operations to be able to run on websites, mobile and embedded devices. MobileNets are small, low latency and low capacity models parametrised to adapt to resource restrictions in different use cases (Howard, 2017). MobileNetV3 is an architecture developed by Google and first launched in 2019. It is an extension of previous versions (MobileNetV1 and MobileNetV2) which uses lots of advanced technology to achieve better performance. It is optimal designed for mobile and embedded vision applications to optimize between performance and accuracy. The small-size and fast-computing model helps to reduce storage requirements and processing capacity and gain excellent results with high accuracy on standard ImageNet dataset without large computational resources (Howard et al., 2019). For the above reasons, MobileNetV3 (both Large and Small versions) is chosen to be the next typical network model representing for MobileNet architecture to conduct the evaluation program to select the best model for the study.

2.3. Related studies on plant detection via images using deep learning techniques

With the dramatic development of AI in general and machine and deep learning techniques in particular, there have been many studies related to "the application of deep learning techniques for image-based plant detection in Mekong Delta. Concretely, there was the study by Thanh and Nghe (2022) on rice leaf disease detection using transfer learning method. The main research direction of these studies was to develop an automatic training model when adding images to detect diseases on rice leaves. The results of the study revealed the four common rice leaf diseases including rice blast, brown spot, leaf blight and thorny beetle, could be detected rapidly and accurately.

Another study by Le et al. (2023) was about the identification of longan types through longan leaves using image and deep learning technology. The purpose of the study is to identify and classify longan types using deep learning techniques with the VGG16 model to train the obtained data. The results achieved the success in identifying 3 types of longan leaves, namely Ido, Thach Kiet, and Dimocarpus Longan Lour with an accuracy of 98.3%. The study by Pham et al. (2022) was on the application of Artificial Intelligence for boosting digital transformation in the field of forest management. The study focuses on using MobileNetV3 convolutional neural network through transfer learning to solve the problem of rare animal and plant recognition which serves for forest management work. The results showed that the model performs well on mobile platforms (iOS and Android) with high recognition accuracy and optimal processing time.

3. PROPOSED METHOD

The above research results offer useful practical knowledge for us to implement the experiment for our research, particularly the application of deep learning for rice leaf disease detection. This study applies deep learning techniques of two main Convolutional Neural Network models including MobileNet (Mobile Network) and ResNet (Residual Network). These models are concerned by computational users and widely used by their high accuracy and performance. Thus, treatments were conducted using MobileNet and ResNet based on an image dataset of three rice leaf diseases including leaf smut, brown spot and bacterial leaf blight to select the best model. The model enables the detection of the above diseases through rice leaf disease images in a fast, effective, and accurate way. This helps efficiently support and create the best conditions for farmers in rice production and cultivation.

In order to build the optimal model for rice leaf disease detection using deep learning, we implement experimental treatments including the main phases as follows:

– **Phase 1:** searching and collecting image dataset of rice leaf diseases standardized on Kaggle to use for testing, and add into MobileNetV3 and ResNet50, then evaluate strengths and weaknesses of each model (including processing speed and the accuracy of the results) finally select the best model out of two above models (Figure 2).

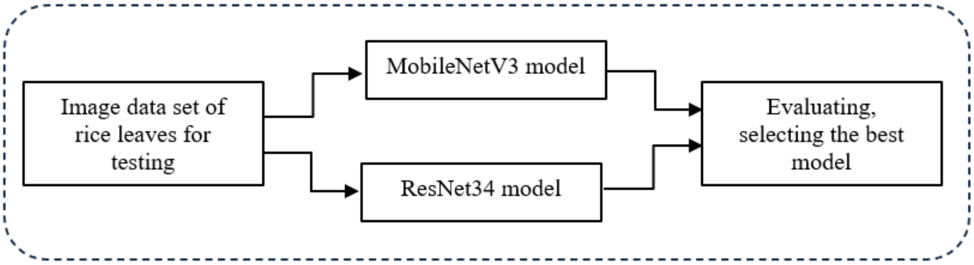

Figure 2. Phase 1 - Selecting the best model for rice leaf disease detection

– **Phase 2:** Building and setting diagnostic model for three rice leaf diseases (leaf smut, brown spot and bacterial leaf blight) based on the best-chosen model (Figure 3).

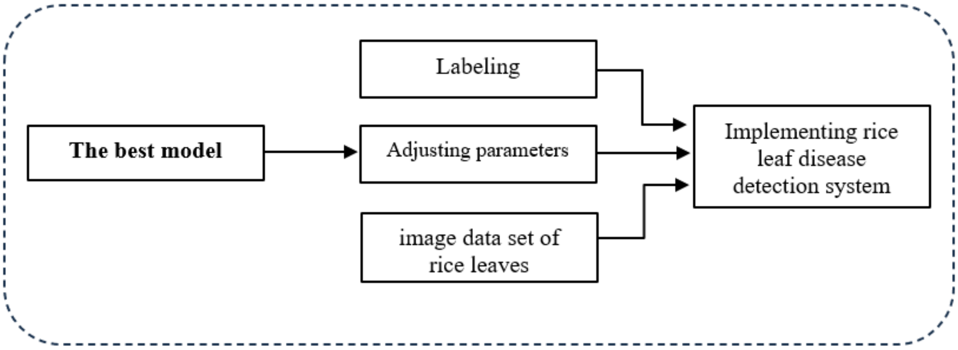

Figure 3. Phase 2 - Building the model for rice leaf disease detection

4. EXPERIMENTAL MODEL

4.1. Experimental data

The training dataset for the model consists of 4.804 images of three diseases (leaf smut, brown spot and bacterial leaf blight) available on Kaggle (a famous online platform for data scientists and people who concerned machine and deep learning where it provides large free and authentic data sets with multiple topics from business, medicine, sport to images and documents. Experimental images were collected with differential angles, quality and sizes (Figure 4).

Figure 4. Illustration of experimental images of rice leaf diseases with different angles, quality and sizes

Table 1. Separation of experimental images

Folders	Bacterial leaf blight	Brown spot	Leaf smut
Train	1316 images	1328 images	1200 images
Valid	164 images	166 images	150 images
Test	164 images	166 images	150 images

After collected, data were synthesized and split into folders mainly train-used for model training, valid-used for validating during training time and test-used for checking the performance and quality of trained model with the ratio of 80% for train set, 10% for valid set and 10% for test set in which each set content three data subsets bacterial_leaf_blight, brown_spot and leaf_smut with same above ratio (Table 1).

4.2. Methodology

After preparing data for ResNet50, MobileNetV3 Large and MobileNetV3 Small, the tested dataset of three diseases was trained with both models, ensuring the same condition when training.

– Using the same experimental dataset saved at training folders with three sets for training, testing and validating;

– Using the same machine to train;

– Using the same software to run the training program: Jupiter Notebook.

The comparison is made based on three criteria which were respectively carried on with epochs 10, 20, 30 and step number 121, mainly as follows:

– Mean accuracy of train and valid sets;

– Mean accuracy and error of test set;

– Complete training time.

After implementing program and training for ResNet50, MobileNetV3 Large and MobileNetV3 Small, the results were synthesized with the following criteria (Table 2).

Discussions:

– Mean accuracy of train set: MobileNetV3 – Large dominates the rest of models in which its three different epochs' accuracy is higher than that of ResNet50 and MobileNetV3 – Small.

– Mean accuracy of valid set: MobileNetV3 – Large dominates on one epoch, while MobileNetV3 – Small dominates the rest of models on three epochs (with epoch 10 for MobileNetV3 Large and MobileNetV3 – Small).

– Mean accuracy and error of test set: all three models have the same ratio of 1.0000 (100%).

– Mean error of test set: with epoch 10 and 20, MobileNetV3 – Large dominates, while ResNet50 dominates with epoch 30.

Complete training time: MobileNetV3 – Small has the shortest time compared to the rest with 20 nearly 20 seconds per epoch.

Table 2. Results of comparing experimental data between MobileNetV3 and ResNet50

Measures of criteria	Epochs	ResNet50	MobileNetV3 Large	MobileNetV3 Small
Mean accuracy of training set	10	0.92146	**0.98473**	0.97908
	20	0.96344	**0.99177**	0.99090
	30	0.98001	**0.99485**	0.99416
Mean accuracy of validation set	10	0.92895	**0.99875**	**0.99875**
	20	0.95156	0.99937	**0.99936**
	30	0.96860	0.99951	**1.00000**
Mean accuracy of test set	10	**1.00000**	**1.00000**	**1.00000**
	20	**1.00000**	**1.00000**	**1.00000**
	30	**1.00000**	**1.00000**	**1.00000**
Mean error, loss of test set	10	3.2838e – 04	9.9357e – 06	3.0741e – 05
	20	5.6754e – 04	9.3519e – 06	5.9691e – 06
	30	**1.8365e – 07**	4.5873e – 06	2.3448e – 06
Training time	10	775.7 sec	41.4 sec	**15.8 sec**
	20	774.2 sec	42.4 sec	**14.5 sec**
	30	773.3 sec	43.23 sec	**19.4 sec**
Ratio of dominating criteria		**4/15**	**9/15**	**9/15**

4.3. Results of comparing and evaluating to select the optimal model

The experimental results from (Table 2) reveal that *MobileNetV3-Large* and *MobileNetV3-Small* dominate *ResNet50* after applying in the study "Building the program for rice leaf detection using deep learning". However, the training time of *MobileNetV3-Small* is very short, but it also ensures high accuracy, reasonable loss and errors. Therefore, the best model used for deep training and implementing the program was *MobileNetV3-Small*.

With the chosen model- MobileNetV3 – Small, the experiment was conducted to detect rice leaf diseases by following steps:

– **Step 1:** pre-processing images: It attributes to strengthen data – an important technique of deep learning to create variants of current training data which helps to improve generalizing capacity of the model.

– **Step 2:** Using pre-trained MobileNetV3 -Small on ImageNet dataset to create a new image classification model.

– **Step 3:** Implementing and training the model with epoch 70.

– **Step 4:** Implementing to draw a diagram of Accuracy and Loss of training per epoch. (Figure 5).

Step 5: Testing results after successfully training the model (Figure 6).

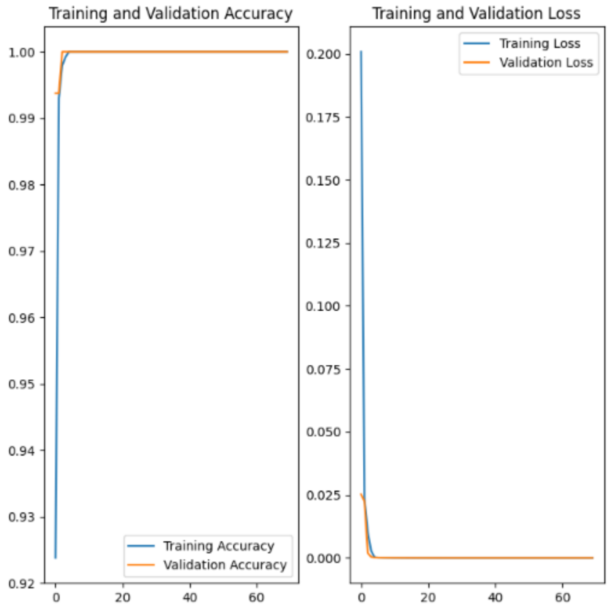

Figure 5. Diagram of Accuracy and Loss of training per Epoch

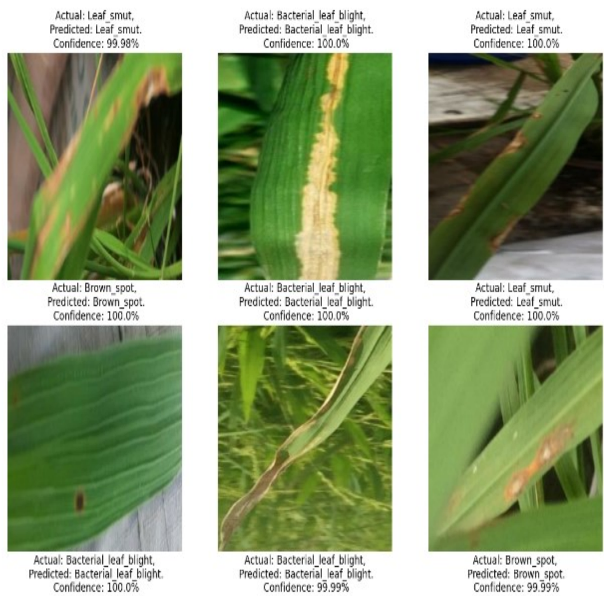

Figure 6. Results after successful training of the model

The experimental findings show that our proposed model offers nearly absolutely accurate results for rice leaf disease detection.

5. CONCLUSION

In this study, we explore several deep learning models commonly used for image-based plant detection, along with a range of popular deep learning techniques. We recommend experimental models for rice disease detection using network architectures such as ResNet50, MobileNetV3-Large, and MobileNetV3-Small to identify the most suitable model for practical application in the Mekong Delta. The findings show that MobileNetV3-Small provided highly accurate diagnostic results for three rice leaf diseases—leaf smut, brown spot, and bacterial leaf blight—within a short processing time. In the near future, our research team aims to expand this work by developing mobile applications to further support real-life rice disease classification. We also plan to build a larger training dataset that includes not only the three diseases studied but also other common rice leaf diseases.

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