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From A Proposed CNN Model to A Real-World Application in Rice Disease Classification

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***Abstract*—A compact and precise application of rice disease classification is helpful to assist farmers in their work for treatment on the plants and therefore could be quick and accurate to measure and eliminate the effects of diseases more profitably. In the past, the works were completed by naked-eye observation and basically relied on the experiences. Even so, the results are quite subjective and heuristic. In this paper, a mobile application to automatically classify several kinds of rice diseases from rice plant images and then to accurately recommend the uses of pesticides or chemicals. To do so, a proposed convolutional neural network (CNN) model is given. The results show that the proposed CNN model achieves the performance with the best trade-off between accuracy and time efficiency in comparison with the state-of-the-art models in our dataset. This model could be easily embedded into a mobile application to process in near real-time processing.**

***Index Terms*—Rice diseases, Mobile app, CNN.**

I. Introduction

In Vietnam, the agricultural sector still plays a key role in the economy. Based on the report of the general statistics office of Vietnam, the sector donated 23.52%[1] to the total economic growth in 2021, proving its role as the important pillar of Vietnam's economy. Among agricultural growth, the rice sector is known as one of the most crucial foundations, it contributes 30%[2] to the overall agricultural production values.

Rice has been grown in Vietnam for about two thousands of years. However, the application of advances in high technology in cultivation is limited and has not kept pace with the world. In many regions, some tasks rely on the manual works with experiences, shown in Figure 1.

In fact, there are several kinds of diseases that directly resulted in the yield losses, sometimes standing at about 15% on average [1]. Therefore, farmers need to detect the diseases and to have effective solutions to eliminate their effects. In the past, these tasks were mostly based on manual inspections, and then to extirpate by the experiences. The works are sometimes not really powerful enough and to be a waste of money. Therefore, the need of automatic rice disease detection and then to recommend optimal solutions from experts are required, which could help farmers make less time and effort, and be more effective than the visual ways of detecting[2].

[1]https://en.nhandan.vn/business/economy/item/10567002
[2]https://www.statista.com/topics/5653/agriculture-in-vietnam/

Fig. 1. Visual examples of how farmers are taking care of their crops.

Thanks to technology development, mobile devices nowadays have become more common in our life. Hence, the images captured from the devices become easier than ever. A mobile application (app) using the images to detect and classify rice diseases would be a great approach. To do so, an accurate and efficient detection machine embedded inside the app has gained lots of attention from the literature, especially with convolutional neural networks (CNNs). Over the past decade, CNNs have led the main trend in research activities over the world with object detection and recognition in particular since the first milestone with the AlexNet system in 2012 [3]. Following that the CNN models have been improved time by time and achieved state-of-the-art results, particularly the agricultural sector [4]. However, these deep architectures and systems are time-consuming and little compatible with a low-level energy consumption architectures [22]. Therefore, proposing an accurate model while adapting well with time constraint, is an open question in literature up to this time.

In this paper, our contributions could be listed.

- A new CNN model is proposed to classify four popular kinds of rice diseases in Vietnam. The model is competitive with the top accurate models of the literature while guaranteeing the best trade-off between accuracy and time efficiency.
- A mobile application (app) is designed where the pro-

posed CNN model is embedded inside. Users can be straightforward to install and use the app. Four kinds of rice diseases are classified and then the app returns the guides about the particular disease and the advice from experts on how to kill it.

The remainder of the paper is organized as follows. Section II discusses the related works in the agricultural domain. Then, section III presents our model and app. Next, section IV shows the experimental results. Finally, section V concludes the topic and gives the future works.

II. Related works

Deep learning techniques have a high performance in image classification recently. Various approaches have been used for recognizing and detecting plant diseases with artificial neural networks (ANNs) [6], Support Vector Machine (SVM) for sugar beet diseases [7] based on stages of disease. Some mango leaf diseases were detected in [8], authors combined low level features (shape and color) and CNN features together, and then applied the SVM to classify diseases. Authors in [9] worked on detecting tea leaf diseases by combining feature extraction [10] and neural network ensemble (NNE).

The DNN-JOA method was proposed in [11]. K-means clustering method was applied for the segmentation process. A feedback loop was employed between the classification and segmentation stages to improve the quality of the classification process. At the end, the proposed approach achieved a high overall accuracy about more than 90% for classifying four kinds of paddy leaf diseases.

Different CNN architectures were implemented in two different training methods to detect four stages of apple black rot from images in the PlantVillage dataset [12]. The first method was created and trained models from scratch while the second method was based on the pretrained models such as VGG16, Inceptionv3, and Resnet50. Finally, fine-tuned VGG16 model played as the best candidate with 90.4% of accuracy on the test set.

It is true that, most of the plant diseases are detected on their leaves. Therefore, authors in [13] provided 79,265 leaf images from various weather conditions, angles, and daylight hours. After that, they proposed a two-stage architecture called PlantDiseaseNet. PlantDiseaseNet combined the AlexNet model as the feature extractor and Yolov3 as the classifier to propose the regions of interest in the first stage. Following that, an architecture like the ResNet architecture was applied to classify plant diseases. The model was achieved an accuracy of 93.67% in the whole dataset.

Besides training model from scratch, the transfer learning technique was commonly used in identifying plant leaf symptoms. The pre-trained VGGNet on the ImageNet dataset and the Inception module for the feature extractor were employed and a new CNN model named the INC-VGGN model was proposed for the class prediction in [14]. This model attained an accuracy of 92% on the their own dataset. Similarly to [14], authors in [15] trained fine-tuned AlexNet and GoogleNet to detect nine tomato diseases from 14,828 raw images of tomato leaves.

In the experiment [16], they compared three famous CNN architectures such as the SVM, ResNet, and VGG models to classify four apple leaf diseases. They conducted that ResNet18 with fewer layers of ResNet achieved better recognition performance.

Many models with efficient techniques were used in those researches mentioned above. They focused on accurate plant disease classification by using various types of deep learning models, especially CNN architecture such as AlexNet, GoogleNet, ResNet, and so on. Some of those used neural network ensemble, while others used SVM, ANN. These studies contributed to accurate classification of plant diseases. In addition, there are recent and strong models proposed for an accurate detection and classification like [21], [22]. Nevertheless, most of them focus on modifying the technique to achieve high accuracy and do not consider the effect of a number of parameters on deploying onto mobile applications.

One of our purposes is to deploy a lightweight mobile application so we need a small-parameter model that can run fast on any platform. Additionally, in some remote areas, the internet connectivity is limited or has slow speed. Hence a memory CNN model is necessary for plant diseases recognition and detection. On the other hand, the reduction of the number of parameters in the CNN model limits the capability of learning, therefore, balancing between memory elements and classification accuracy is significant.

To deal with this problem, we proposed a new CNN model that achieved high accuracy despite its tiny number of parameters. We performed many experiments on the MobileNetv3 model [20] with a special attention on the MobileNetv3-small version, the DenseNet201 model [17] and the SimpleCNN model in [18]. Finally, the results show that our proposed CNN architecture surpasses the three models for classifying four rice plant disease classes.

III. The proposed system

In the paper, we propose an end-to-end system. The main purpose is to classify the rice diseases from the app. For convenience, Fig 2 shows our approach. Our contribution here is to design a new CNN model which guarantees the best trade-off between the accuracy and time efficiency. This makes the model reasonable to embed inside the app. Our approach is inspired from the Simple CNN model [18]. To avoid underfitting, we increased model complexity by adding one convolutional layer.

For the illustrative purpose, Figure 3 presents the model with six convolutional layers, followed by Batch normalization and MaxPooling2D layers to extract features. For classifying the rice diseases, we employ the three layers for fully-connected components.

As the second contribution, the mobile application is designed to embed the proposed CNN model inside. When the trained model is obtained by the Keras framework[3],

[3]https://keras.io/

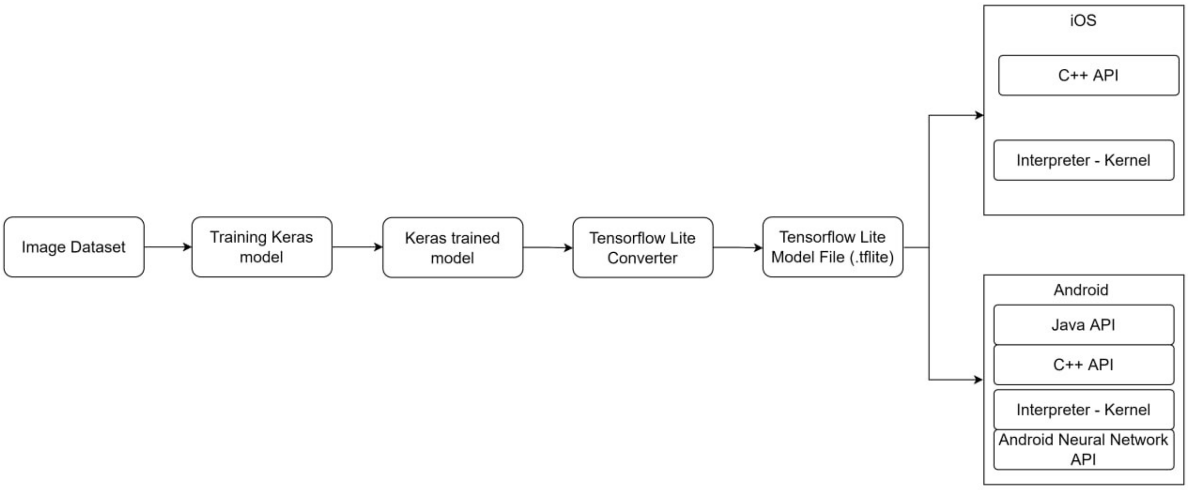

Fig. 2. Our proposed system was developed to classify rice diseases.

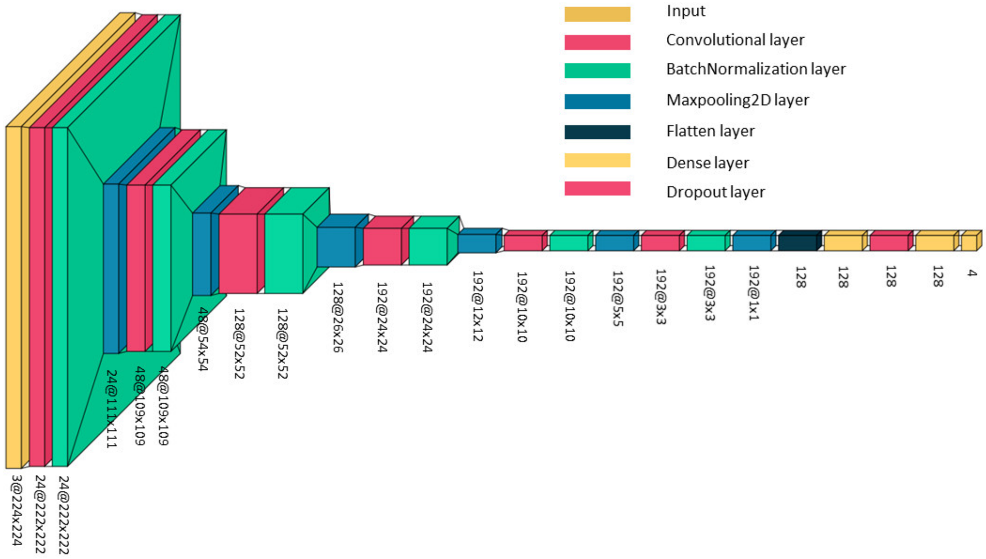

Fig. 3. The proposed CNN model for classification of rice diseases.

it is converted into the TFLite model[4] before deployed in mobile devices. In order to identify and clarify the system requirements, we present here a general use-case diagram for our mobile application in Figure 4.

User could upload or take directly images from smartphones. The app will predict the images and then return the results. User can look at the results of prediction and take a deeper view on the related information and how to treat the corresponding disease. With the extended action, as soon as classified objects are obtained, the correct results will be uploaded to the server. By doing so, it tends to enrich the dataset, known as a key factor to upgrade the proposed model in the next time. In addition, as soon as users take or upload images from smartphones, the timestamp and location will be recorded by the system and saved to the database with the result of the prediction in order that they can accurately handle the disease and track the progress of the treatment. As one of the advantages, it could be a reference for the experts to give their advice on the progress of treatment.

Administrator chooses the best model which suits well with data while updating the information related to the kinds of

[4]https://www.tensorflow.org/lite/guide

diseases. Furthermore, administrator also could retrain the model during the period of time to update with the new samples of data.

With the assumption that most of users are farmers and they may have less knowledge about new techniques. Therefore, should they retrain or select a model without understanding about images, they may get unexpected results. Therefore, we have restricted their right to retrain or update the model. In the next perspective, we could add more features such as a social community so that users can interact with each other for further information.

Moreover, user could interact with user for further information about the specific rice disease, and then give their advice if necessary. In addition, expert also update information or suggest new techniques to treat the diseases.

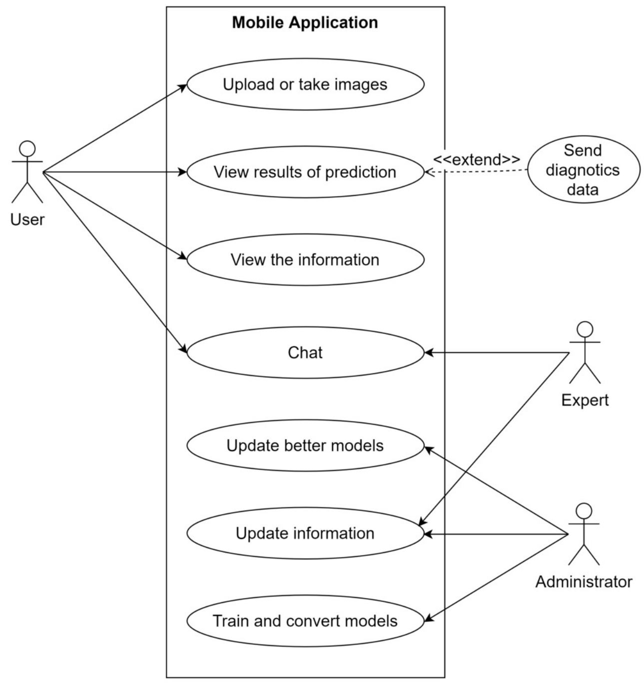

Fig. 4. The general mobile application use-case diagram.

IV. Experimental Results

In this section, we will evaluate the performance of our proposed model against some well-known models. To do so, section IV-A shows the standard dataset while section IV-B presents the environment setups for experiments and the parameter configuration. At last, section IV-C discusses the results.

A. Dataset

For evaluating the proposed model, we use the dataset in [19] which includes 5932 images of four kinds of rice diseases: Bacterial blight, Blast, Brown Spot and Tungro, shown in Table I. Some images from the dataset are given in Figure 5. Based on our experiences, this dataset is large enough to evaluate the performance of the proposed model. In the real deploying process, the proposed model could be periodically retrained to fit well with each region. The dataset is divided into 3 sets with 60% for the training set, 20% for the validation set, 20% for the test set. This division is resulted of several training and testing experiments

TABLE I
Rice Leaf Disease Image Samples.

Class name	Number of images
BacterialBlight	1584
Blast	1440
Brownspot	1600
Tungro	1308

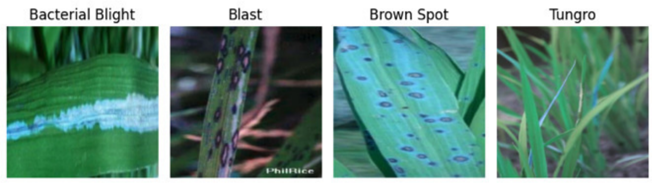

Fig. 5. Images are extracted from the dataset [19].

B. Protocols

To make the performance evaluations are fair enough, we employ the MobileNetv3-small [20], DenseNet201 [17] and SimpleCNN in [18] models in the experiments. All models were trained by baseline learning from scratch. To be more detailed, some configurations of the training process could be listed as optimization algorithm: Adam; learning rate: 0.001; the number of epochs: 120; the loss function: categorical-crossentropy; data augmentation techniques: Rotations, Shifts, Flips, Brightness, Zoom.

For metrics of evaluation process, we employ accuracy and a confusion matrix as the standard metrics. Accuracy measures the number of true classifications over the total number of classifications. A confusion matrix presents the performance of the model where the model is embarrassing when it gives predictions.

Thanks to Google colab notebook[5], all of our experiments for the training and testing of the models were implemented here.

C. Results

For the training set, Figure 6 indicates how well the models have suited with the dataset. As illustrated, the Simple CNN does not perform well with the dataset while the DenseNet201, MobileNetv3-small, proposed models tend to converge.

In the test set, Table II shows the results of the proposed model against other models with the accuracy metric. The DenseNet201 model is the best classifier with 99.65% followed it by the proposed model with 99.21%, the MobileNetv3-small model with 91.3%. However, it is worth

[5]https://colab.research.google.com/

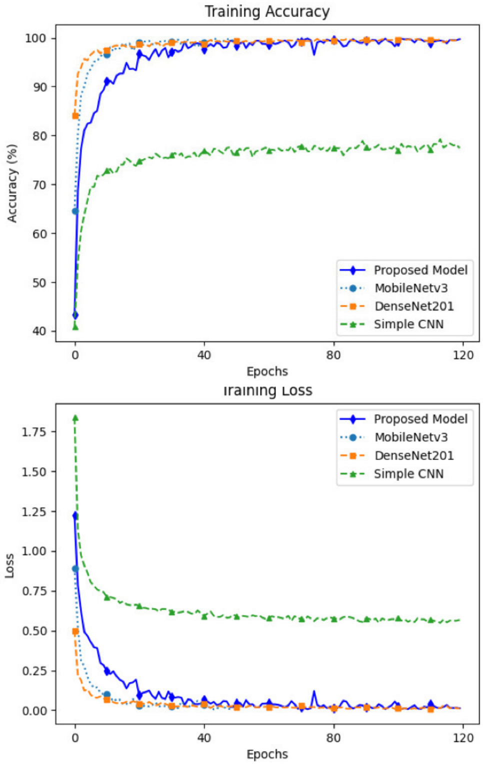

Fig. 6. The training accuracy and training loss among models on the selected dataset.

noting here that the number of parameters of the DenseNet201 model is about 25 times as much as the proposed model. The SimpleCNN model is quite slight, however, it performs a bit poorly in this dataset.

TABLE II
THE PERFORMANCE EVALUATION OF THE PROPOSED MODEL AGAINST OTHER MODELS.

CNN architecture	Number of Parameters	Accuracy
DenseNet201	20 millions	99.65%
MobileNetv3-small	3 millions	91.3%
SimpleCNN	0.276 millions	75.1%
Proposed Model	0.8 millions	99.21%

Figure 7 shows the ability to classify four kinds of the rice diseases. The results prove that the proposed model fits completely with the dataset.

Within the mobile app, we accomplished to deploy the proposed model in both operating systems such as: iOS and Android. Figure 8 shows the returned results from the app. For the average processing time, we measured on Redmi Note 9S[6]. In total with one image, it is about 0.11 seconds with 0.03 seconds in the image processing step and 0.07 seconds in the image classification step. It demonstrates that the app could respond mostly in near real-time processing.

[6]https://www.mi.com/global/redmi-note-9s/specs

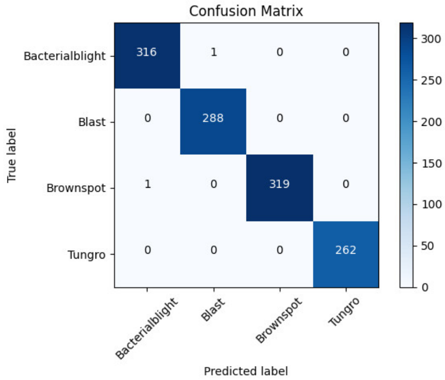

Fig. 7. The confusion matrix of the proposed model on the test set.

V. Conclusion and Future Works

The main contribution of the paper is to present a novel CNN model for rice disease detection with the best trade-off between accuracy and time-efficiency. Our proposed model is competitive with some state-of-the-art models when obtained about 99.21% in accuracy on the dataset of rice leaf diseases [19]. Moreover, with near 0.8 millions of parameters, our model appears as the top slight architecture. It guarantees the ability to deploy into low-cost hardware architectures. As a case study, we successfully embedded the model into the mobile app within iOS and Android operating systems. It allows users to automatically detect and give the detailed information for each rice leaf disease without the Internet.

As perspectives, the proposed model could be updated in order to detect more kinds of diseases corresponding to each specific cycle of diseases. In addition, the app would allow users to directly retrain the model by themselves from uploaded images. Due to some administrative procedures, the complete mobile app will be available on Google Play Store and App Store soon.

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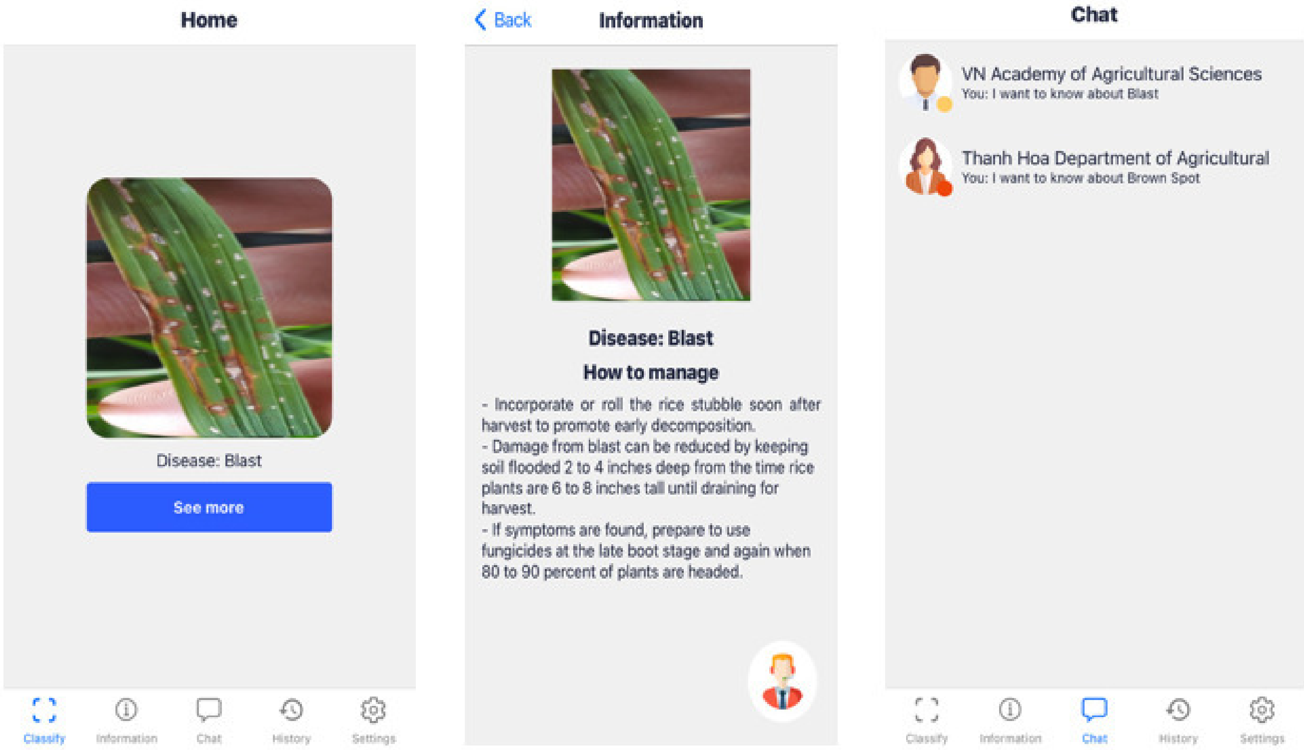

Fig. 8. Visual examples of the mobile app for classification and then to show the detailed information, or to contact with the expert.

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