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Applying Multiple Deep Models to Predict Plant Pests in Advanced Agriculture

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ABSTRACT

Nowadays, advanced sciences and technologies have been wide applied to smart agriculture fields. There are many challenges to agricultural companies, and scientists. So that it is important task to investigate a solution to detect early of plant pests and diseases for appropriately treating to product green agriculture products with least environmental impacts. This paper presents a proposed approach for applying artificial intelligence, deep learning specifically, to classify some plant pests and diseases. We have investigated a number of deep architectures of machine learning for effective solution for pests prediction through agriculture images. Some deep neural models are studied to apply for feature extraction task. Particularly, we surveyed and experimented based on some well-known architectures such as ResNet, EfficientNet, MobileNet, NASNet. In the classified part, we proposed the use of fully connected neural network. To evaluation and analyze the performance effectiveness of the proposed approach, we collected plant image pests and diseases in agriculture circumstance. Dataset consists of 3,391 samples within 6 categories of plant pests and diseases. Generally, there is also imbalance problem of the plant pest samples in some categories. Therefore, we also applied data augmentation solutions to improve the accuracy of the prediction system. Experimental results show that the pest prediction approach based on deep learning techniques reaches high accuracy. Among of them the feature extraction backbone based on ResNet101 conducts the highest results with the ratios of accuracy, precision, recall, specificity and F1 are 99,25%, 97,84%, 97,83%, 99,53% and 97,82%, respectively.

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1. Introduction

Nowadays, the artificial intelligence and IOT techniques have been promptly developed, deep learning has been widely applied in advanced agriculture such as environmental information analysis, plant production monitoring. With the applying techniques to the digital transformation and agriculture product tracking, consumers can access and know this information in real time circumstance… Beside of that, the use of pesticide, widespread to prevent pests in inappropriate approach led to a huge impact on the environment, unsafe products, low productivity, costs increasing, and so on. Amount of them, computer vision techniques have also been widely applied in many fields of agriculture such as plant categorical inspection, obtaining information about crop growth status, auto harvesting, detecting pests and diseases for treatment, plants, product quality monitoring and agriculture products classifying. In particular, the farmers in some zones recognize pests and diseases, fertilize crops based on their knowledge and experience leading to incorrect prediction of pests and diseases that causes crops fail. Additionally, manual data processing, that takes a lot of effort but low precision. In the field of the computer vision based expert systems, there are some plant pests classification methods using deep learning are applied in real agricultural practice. Recently, some disease diagnosis systems, which based on deep learning method, reached higher levels. As an evident, plant pests diagnosis methods based on deep learning have becomes an important research field, and commercial applications [1]. However, application of deep learning technologies to plant diseases and pests detection has become big issue concern to researchers, who are experts agricultural knowledge but amateur in artificial intelligence, machine learning. Therefore, in modern agricultural reach has becomes multiple disciplines.

2. Related works

There are some well-known approaches for pattern recognition in high accuracy and fast computing, especially the CNN approaches such as GoogleNet [2], Microsoft ResNet [3], Fast R-CNN [4], Faster R-CNN [5]. Some research groups focus to improve feature extraction task, such as [6-9]. Most of them efforted to customize classified models by combination of some machine techniques, such as SVM, neural network and so on. Other researches try to optimize hyperparameters for training with expected improve effectiveness of CNN models by applying some searching methods [10],[11]. In the field of rice plant disease prediction, research on model for automatically identify crop diseases, authors in [12] presented a method based on deep learning. Their module supports for inspecting pests in harsh environments. An approach for crop pests classification based on multi-scale feature fusion was presented in [13]. They proposed a network mode using multi-layer dilated convolution for feature extraction module with expected to extract more information without increasing the number of parameters. Authors in [14] presented an efficient approach for plant pests classification using new deep learning architecture, namely Deeppestnet. The architecture model consists of eight convolutional learnable layers for feature extraction and three fully connected layers for classifier. The proposed method was evaluated on special dataset and produced high accuracy. Beside of that, an approach based on CNN ensemble for plant disease and pest detection, which named PlantDiseaseNet, was presented in [15]. The system consists of the deep neural networks backbone for feature extraction stage and support vector machine (SVM) classifier for classification stage. They experimented approach by fine-tune with six state-of-the-art CNN. Their experimental results on the private dataset demonstrated that their approach reaches state of the art results. Another group of authors in [16] presents an approach which is also based DCNN for classifying of rice plants based on the status of rice health using images of its leaves. The model is transfer learning from AlexNet pretrained model. Their approach achieved 91.23% accuracy based on gradient descent probability under parameter setting 30 of mini batch size and 0.0001 of initial learning rate. Authors in the article [17] presents an approach for automatic diagnosis of pests and diseases based on genetic algorithm . The approach using three types of feature extraction, textural descriptors using gray level co-occurrence matrix. The paper [18] presents a method for detecting plant diseases based on machine learning and image processing techniques. In their method, the SVM machine combining with deep CNN for diseases classifying. Their experimental results on diseases classification and identification achieved 97.5% accuracy. Authors in [19] presented a deep feature extraction and SVM classification for rice leaf disease diagnosis. That method reached high results when applied on dataset, which consists four types of rice leaf diseases with 5,932 images. There are four diseases categories of brown spot, bacterial blight, blast, Tungro. Some tiny deep architectures, mobilenet and shufflenet were evaluated. The experimental results illustrated that the deep CNN + SVM outperform in comparation to transfer learning.

This work proposes a solution for automatic detection pests to advise and recommend the pest treatments in advance. This task is expected to bring an efficiency to farming, increasing product quality, and making a sustainable income for farmers, agriculture company profits.

3. Proposed approach

The overview architecture of the pest prediction and recommendation system is shown in Figure 1. The solution consists of some steps data preprocessing to extract regions of interest (RoI), data augmentation to solve the data imbalance problem, surveying some feature extraction models based on the well-known backbone such as ResNet, EfficientNet, MobileNet, NASNet. In the classification task, the fully connected network is designed. As mention above, the pest prediction results are used to recommend to farmers how to treat or automate pest treatment without manual human in advanced systems.

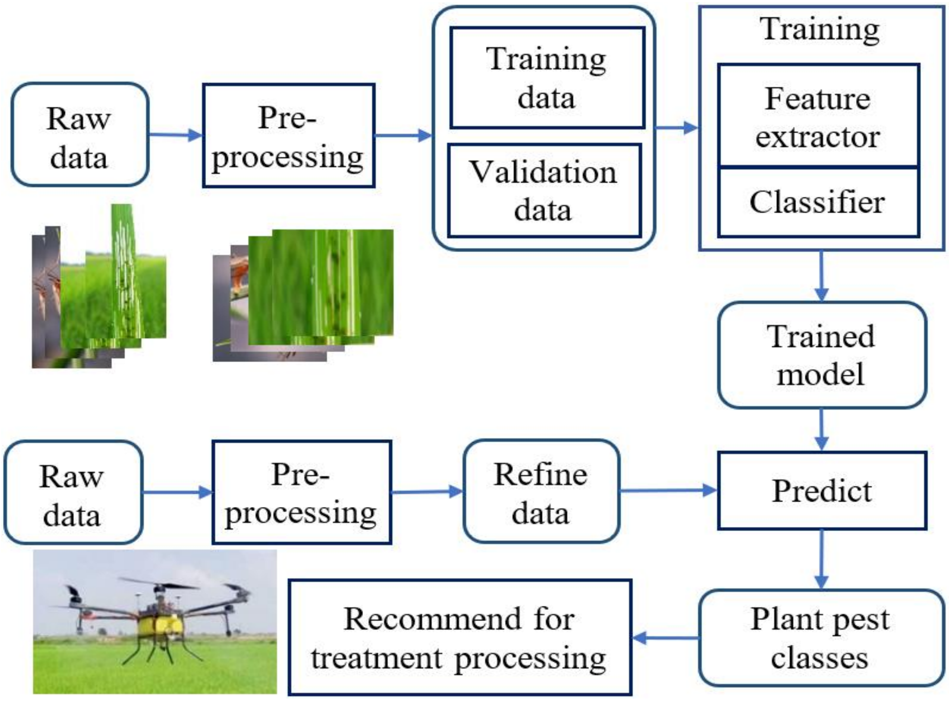

Figure 1. *General flowchart of the system*

Data preprocessing: The region of interesting (ROI) samples are extracted from the raw image dataset, which supports to focus on pest areas. The ROI samples are normalized and resized to 244x244 images. Data augmentation techniques are applied by using some geometric transformations, the spectrum normalization to adapt to different lighting conditions.

Training model: In the feature extraction part, to objectively evaluate the influence of network architectures, we investigated some commonly architectures of feature extraction backbone such as ResNet, EfficientNet, MobileNet, NASNet. General speaking, the feature extraction backbone can be based on pretrained models or defined based on the basic DCNN. The output of this block is the feature map as input to the classification block. The model parameters of pretrained models are transformed for training on our dataset. In this study, we also customized some extrinsic hyperparameters for improving the accuracy. These architectures are representative for different kind of neural networks. MobileNet is a small deep learning architecture. ResNet is more complex architectures based on the basic inception architecture. Meanwhile, EffientNet or NASNet are very deep and large architectures. The fully connected network consists of 2 fully connected layers with each layer of 512 nodes combining with the ReLu activation function and Dropout layer with 50% selection probability. The softmax function is used for last layer of the classifier. To solve the problem of the multi classifier, we applied the error function according to the categorical-cross entropy approach. The experimental results also illustrated that the categorical-cross entropy function leads to more stable results than other loss functions, e.g. log cos, mean squared, cosine similarity, mean absolute, mean squared, …

4. Material and Data processing

4.1. Data collection and processing

Plant images are captured by agricultural officer in many locations. This task is collaborated with farmers, who are cultivating crops and agricultural. Image data brought to the branch of Cultivation and Plant Protection-the Department of Agriculture and Rural Development of An Giang province with more than 5,000 images of 10 diseases on variety periods. Image set was captured by using variety devices such as mobile phone, mini camera and EOS DSLR camera. Images were token in different time and different places. The poses of camera and optical lens are not fixed how to focus to the pests region. They are analyzed, filtered, and classified by agricultural experts. Due to difference of plant pests with difference the number of samples in pest categories, we selected 3,391 image samples of six kinds of

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the popular pests, which are Aleurocybotus indicus, Leptocorisa oratoria, Bacterial leaf blight, Cnaphalocrocis medinalis, Dicladispa armigera, Orseolia oryzae. Some examples of rice pests are demonstrated in Figure 2.

Data preprocessing: Image dataset is collected at specialized agricultural departments, agricultural experts carry out screening and classifying by disease kind and disease period to create the image database, diseased labeling data samples. They removed unsatisfactory image samples such as: unclear detail of object, capturing too far away, loss focusing to harmful objects. This first step is very important, because it utilizes to eliminate most of the error images. The collected image dataset are transformed, normalized, and brought to the most favorable form suitable for the input of analysis and processing techniques. All image are converted to the uniform format.

Figure 2. *Some image examples of plant pests*

4.2. Experimental material

According to the data processing in above step, the experimental data consists of 3,391 image samples of six pest categories, that are Aleurocybotus indicus, Leptocorisa oratoria, Bacterial leaf blight, Cnaphalocrocis medinalis, Dicladispa armigera, Orseolia oryzae. The dataset is separated to 70% for training and 30% for testing. The details of dataset is illustrated in Table 1.

Table 1. *Details of the experimental dataset*

	Training set	**Validation set**	**Test set**	**All**
Aleurocybotus indicus	305	33	144	482
Leptocorisa oratoria	435	48	206	689
Bacterial leaf blight	421	46	200	667
Cnaphalocrocis medinalis	423	47	201	671
Dicladispa armigera	231	26	109	366
Orseolia oryzae	326	36	154	516
Total	2141	236	1014	3391

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5. Experiment and Analysis

5.1. Performance evaluation

In this study, some metrics are used for evaluating and comparing the performance of some models, which are based on difference of feature extraction backbones. The performance of the models is evaluated by five evaluation measures, Recall (REC), Accuracy (ACC), Precision (PRE), Specificity (SPE), and F1. This problem is related multiple categories. Therefore, the evaluation formula is different from the binary classified problem. The metrics are measured according to one class versus other retain classes. That is, when calculating measure values for each class, the class is counted as positive samples and the remaining classes are considered as negative samples. Among of that, the accuracy criterion is more influence. The effectiveness measured metrics are computed as follows:

Accuracy is used to illustrate the performance measure. This is a simple ratio to measure correction of prediction on the total observation samples. The accuracy of class i^{th} is computed as

$$ACC_i = \frac{TP_i + TN_i}{Ns} \tag{1}$$

where *Ns* is the number of all samples in dataset, $Ns = TP_i + FP_i + FN_i + TN_i$. TP_i and FP_i are is the number of true positive and false positive samples, which belonging to the class i^{th}, respectively. FN_i and TN_i are the number of false negative and true negative samples belonging to the class i^{th}, respectively. The number of negative samples N_i of class i^{th} counted by the total sample *Ns* subtracting to the number of positive samples *Pi*.

$$ACC = \frac{1}{Ns}\sum_{i=1}^{c} n_i * ACC_i \tag{2}$$

where N is the number of samples in dataset, n_i is the number of samples of class i^{th}.

Recall refers to true positive rate, which is named as **s**ensitivity. It is the corrective ratio of positive sample prediction to all actually positive samples.

$$REC = \frac{TP}{TP + FN} \tag{3}$$

Precision refers to positive predictive value in both correction and mistake positive recognition. This mean that is intuitive for the correct ratio of positive prediction to all positive observations. The high precision rate is related to the small false positive ratio. In multiple classes, *TP* refers to the true positive

$$\text{Prec} = \frac{TP}{TP + FP} \tag{4}$$

Specificity refers to true negative rate. It is the proportion of those who received a negative result on this test out of those who do not actually have the condition

$$\text{Spec} = \frac{TN}{TN + FP} \tag{5}$$

F1-Score: The harmonic average of the precision and recall. Therefore, this score measures the effectiveness of identification when just as much importance is given to recall as to precision.

$$\text{F1} = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \tag{6}$$

5.2. Parameters and model training

As mentioned above, the prediction system is constructed based on some well-known feature extraction backbones combining the last stage of classifier. In this experiment, the feature extraction backbones are MobileNet, NASNetMobile, ResNet50, ResNet101, EfficientNetB0, EfficientNetB4, EfficientNetB7. Some hyperparameters and training processing time are shown in Table 2. The classifier consists of 2 fully connected layers with each layer of 512 nodes. All of classifier models are trained with the same extrinsic parameters, such as the learning-rate is $1e^{-4}$, the drop-out rate is 50% of the dropout layer before the softmax layer for classification, the ReLu method is used forr activation function. The models were trained the hardware computer GPU 32 cores 3200Mhz with 2 GPUs with 32GB.

In this study, we investigated the performance comparison of different backbones with fixed the number of training iteration 100 epochs. Table 2 illustrates that the model using the mobileNet backbone has the smallest layer number, parameters and the fastest trained processing. Meanwhile, the model based on the EfficientNetB7 backbone has the largest number of layers, parameters and training time. In fact, the training time is not so important, but predicted time in real application is most important. However, resource usage requires to be considered in the case of the model need to be frequently retrained.

Table 2. *Training models with different backbones and their parameters*

Model with backbones	Number layers	Number parameters	Training time (msec)
MobileNet	90	3,756,742	1,507,280
ResNet50	179	24,639,878	2,614,742
ResNet101	349	43,710,342	4,291,833
NASNet	773	4,813,978	2,821,063
EfficientNetB0	241	4,708,521	2,373,003
EfficientNetB4	478	18,594,917	5,358,193
EfficientNetB7	817	65,411,997	12,577,759

5.3. Experimental results

Experimental results on our dataset about plant pests show that all criteria for evaluating the effectiveness of models, products high accuracy, which reach over 93% to more than 99%. The synthetic comparing results of experimenting different backbones on the criteria of Recall, ACC, Precision, and Specificity are shown in Figure 3, and Figure 4.

According to training progress and cross validation, they illustrate that the model based on ResNet architecture is converged faster than other architectures. The model reaches asymptotic accuracy of 100% after about 40 epochs. Meanwhile, the models based on EfficientNetB0 and EfficientNetB4 are slowly converged, with after 100 epochs tends to reach saturation. Similarly, the validation results also figure out that the ResNet model is strongly stable after about the first 15 epochs reaching over 85% accuracy. General speaking, the models using EfficientNetB0, EfficientNetB4 reach lower accuracy and instability. The model using MobileNet and NASNet architectures performed well but are still inferior in comparing to RESNet101 and EfficientNetB7 ones. In practical, EfficientNetB7 architecture is very deep and spend a lot of time for processing than RESNet101 architecture.

To evaluate the effectiveness, the models based on different backbones, the trained models were tested on testing dataset, which consists of 1,014 image samples, see also Table 1. The details of evaluation results are shown in Figure 5. Each sub-figure illustrates to the confusion matrix of predicting pest categories. The order numbers from 1 to 6 are corresponding to the plant pests of Aleurocybotus indicus, Leptocorisa oratoria, Bacterial leaf blight, Cnaphalocrocis medinalis, Dicladispa armigera, Orseolia oryzae. The experimental results are presented in the confusion matrix showing that the ResNet101 model products the lowest error and miss prediction rates.

Table 3 presents the summary of compared results using models based on seven different backbones according to the following criteria as Recall, ACC, Precision, Specificity, F1. Experimental results on the same image dataset show that the model based on ResNet101 backbone results the highest accuracy comparing to other backbones.

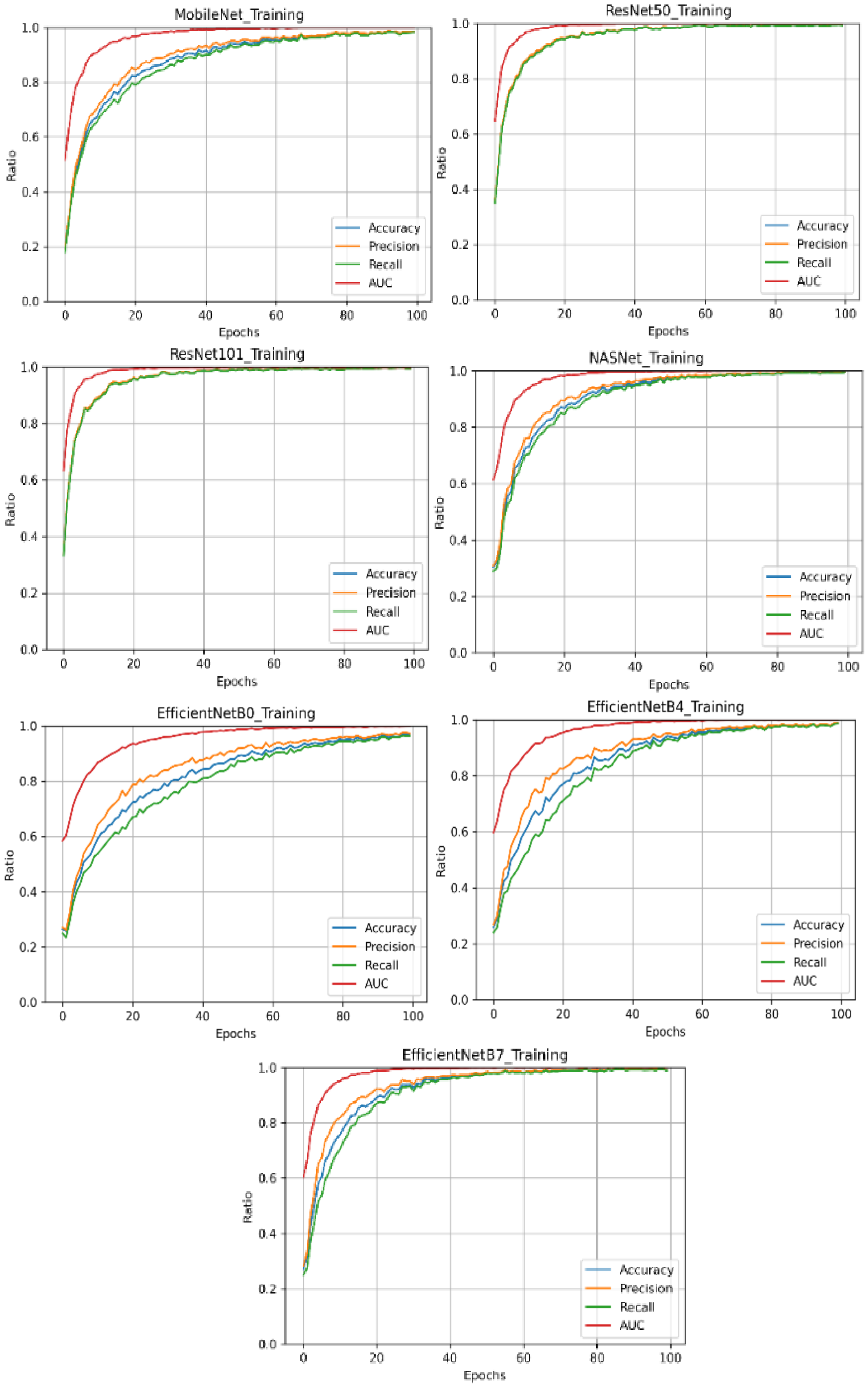

Figure 3. *Performance on the training set*

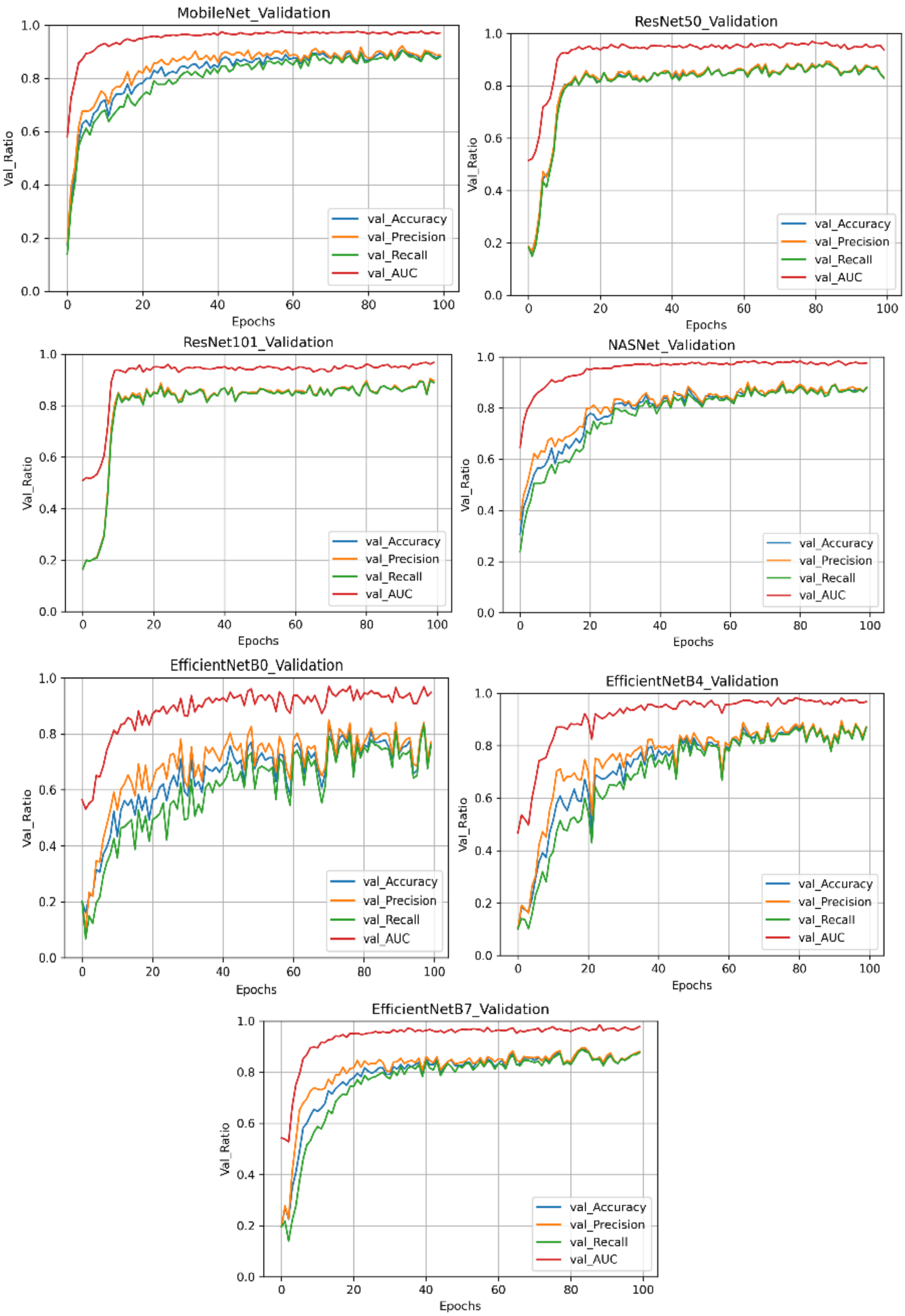

Figure 4. *Performance on the evaluation set*

MobileNet

143	0	0	0	0	1
0	**203**	2	1	0	0
1	0	**197**	2	0	0
1	1	1	**196**	1	1
2	2	5	4	**94**	2
0	12	0	3	0	**139**

ResNet50

144	0	0	0	0	0
0	**199**	1	4	2	0
0	2	**196**	2	0	0
0	4	1	**195**	1	0
0	2	4	2	**101**	0
0	7	0	0	0	**147**

ResNet101

144	0	0	0	0	0
0	**201**	1	3	0	1
0	1	**196**	2	0	1
2	1	1	**196**	0	1
3	1	2	1	**102**	0
0	0	0	0	1	**153**

NASNet

144	0	0	0	0	0
0	**199**	1	5	0	1
0	0	**196**	3	1	0
3	3	0	**195**	0	0
1	1	5	6	**96**	0
0	6	0	2	1	**145**

EfficientNetB0

144	0	0	0	0	0
1	**195**	2	6	0	2
2	1	**190**	2	2	3
9	2	3	**179**	6	2
2	3	5	6	**91**	2
1	7	0	1	0	**145**

EfficientNetB4

144	0	0	0	0	0
1	**201**	3	1	0	0
0	0	**198**	1	1	0
1	1	2	**192**	2	3
0	1	3	1	**103**	1
0	3	2	0	1	**148**

EfficientNetB7

144	0	0	0	0	0
0	**204**	1	1	0	0
0	1	**194**	3	2	0
1	3	0	**196**	0	1
0	1	2	5	**101**	0
0	5	0	0	0	**149**

Figure 5. *Confusion matrixes of the evaluated results on testing dataset using seven models*

Table 3. *Compared results using different backbones*

	Recall (%)	ACC (%)	PREC (%)	SPEC (%)	F1 (%)
MobileNet	95.86	98.61	95.95	99.04	95.81
ResNet50	96.84	98.87	96.90	99.25	96.85
ResNet101	**97.83**	**99.25**	**97.85**	**99.53**	**97.82**
NASNet	96.15	98.67	96.23	99.11	96.14
EfficientNetB0	93.10	97.65	93.12	98.57	93.05
EfficientNetB4	97.24	99.05	97.26	99.41	97.23
EfficientNetB7	***97.44***	***99.10***	***97.47***	***99.40***	***97.43***

6. Conclusions

In this study, we focus on some tasks which include creating database of plant pests and diseases then some image analysis techniques are applied to process the image collection to build the experimental dataset. We also analyzed, explored the feature extraction backbone architectures to build models to predict plant pests and diseases. The task of collection and creation of experimental dataset that requires a lot of effort due to it is depends on the season and the time of plant pests and diseases occurrence. Furthermore, the task of classifying plant pest and disease samples that demands knowledge of agricultural experts with absolute accurate requirements. Experimental results show that the predicted models results high accuracy. In particular, the model based on ResNet101 products the best results under different measurements with 97.83% recall, 99.25% accuracy, 97.85% precision, 99.53% specificity, and 97.82% F1. Experimental evaluation on the natural scene of dataset shows that the proposed approach is outperformance. The experimental results also illustrated that it is possible to apply deep learning techniques to automatically predict plant pests in advanced agricultural systems.

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