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Peanut leaf spot disease identification using pre-trained deep convolutional neural network

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ABSTRACT

Reduction of quality and quantity of agricultural products, particularly peanut or groundnut, is usually associated with disease. This could be solved through automatic identification and diagnoses using deep learning. However, this technology is not yet explored and examined in the case of peanut leaf spot disease due to some aspects, such as the availability of sufficient data to be used for training and testing the model. This study is intended to explore the use of pre-trained visual geometry group–16 (VGG16), visual geometry group–19 (VGG19), InceptionV3, MobileNet, DenseNet, Xception, InceptionResNetV2, and ResNet50 architectures and deep learning optimizers such as stochastic gradient descent (SGD) with Momentum, adaptive moment estimation (Adam), root mean square propagation (RMSProp), and adaptive gradient algorithm (Adagrad) in creating a model that can identify leaf spot disease by using a total of 1,000 images of leaves captured using a mobile camera. Confusion matrix was used to assess the accuracy and precision of the results. The result of the study shows that DenseNet-169 trained using SGD with momentum, Adam, and RMSProp attained the highest accuracy of 98%, while DenseNet-169 trained using RMSProp achieved the highest precision of 98% among pre-trained deep convolutional neural network architectures. Furthermore, this result could be beneficial in agricultural automation and disease identification systems for peanut or groundnut plants.

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1. INTRODUCTION

Peanut (*Arachis hypogea L.*) is one of the commercially important legumes cultivated by local farmers in the Philippines [1]. However, low production is associated with low yielding variety, lack of high-yielding adaptive cultivars, pests and diseases, poor agronomic practices, climate change, and limited use of inputs [2]. Considering peanut diseases, the most common that affect the production are sclerotina blight, late leaf spot, northern root-knot nematode, spottedwilt, stem rot, early leaf spot, rust, web blotch, diplodia collar rot, funky or irregular leaf spot, rhizoctonia limb rot, cylindrocladium black rot, aspergillus crown rot, and peanut root-knot nematode [3]. Among these diseases, early leaf spot and late leaf spot are the most typical peanut diseases due to the warm and humid climate of the country [4]. Leaf spot disease results in increased defoliation and yield losses of up to 50% [5]. Reduction of quality and quantity of agricultural products like peanut can possibly be solved through early detection and regular monitoring of diseases. Yet, this is difficult to be achieved, since detection of peanut diseases such as leaf spot disease is usually done by manually examining and monitoring some changes in morphology or physical traits. Efficiency in doing monitoring is a major problem in most areas in the country due to limited manpower to do the task [6].

Meanwhile, the issue of early detection and surveillance is commonly treated using deep convolutional neural network in plant disease identification because of its nature [7]. The primary purpose of a deep convolutional neural network or deep convolutional neural network is to learn data characteristics from convolution operations [8]. The complexity of the architecture and its capability to provide a higher accuracy model make the deep convolutional neural network, the newest and hottest topic in image recognition [9], particularly in disease identification [10].

Deep learning convolutional neural networks differ from conventional neural networks (CNN) in the sense that they have more nodes and more complex means of layer interconnection [11]. Due to its structure, training a deep convolutional neural network requires high computing power [12] and a large amount of data in order to attain better results [13]. This technology, however, is not yet used, explored, and examined in the case of peanut farming [14], particularly in the identification of peanut leaf spot disease due to aspects such as the availability of sufficient data needed to train and test the model [11].

The purpose of the study is to explore the use of transfer learning algorithm [15], isolation or background elimination [7], and deep learning optimizers in order to address the insufficient data problem in creating a model that can identify leaf spot disease [16]. Specifically, it aims to: gather images of peanut or groundnut leaves, perform pre-processing of the images, perform transfer learning training on the images using different architectures, optimizers, and learning rate to design classifications, and evaluate the models. The contributions of this study are the locally collected dataset and the method used in order to achieve the best model for peanut leaf spot disease identification. This study also explores the use of comprehensive evaluation on the different pre-trained deep CNN architectures, including the application of the different deep learning optimizers. The articles are presented as follows: section 2 explains the overall methodology applied in the study, the experimental set-up, data gathering, data pre-processing, training, and evaluation; section 3 presents the results of the study during training and evaluation; and section 4 provides the conclusions and recommendations.

2. THEORETICAL BACKGROUND AND RELATED RESEARCHES

2.1. Peanut industry of the Philippines

In the Philippines, the National Capital Region is home to the majority of the country's peanut industries, while provincial areas in Luzon and Mindanao are home to the remaining micro-scale producers [1]. Despite of rising local and global demand for peanut finished products, local farmers are still unable to meet the industry's demands, forcing local peanut product makers to import raw peanuts from other countries. Inability of the local farmers to meet the demand is attributed to low yielding variety, lack of high-yielding adaptive cultivars, pests and diseases, poor agronomic practices, climate change, and limited use of inputs [2]. When it comes to diseases, early and late leaf spot is attributed to defoliation leading to yield loss of about 50% and more [3]. This disease is common the country due to its humid weather in most parts of the country in specific month of the year [4].

2.2. Computer vision and agriculture

As computational systems developed, application of machine learning to computer vision achieved exponential growth leading to the development of novel methodologies and models [17], which now form a new category, that of deep learning [18]. These methodologies and models are now used for detection and accurate identification of diseases in grain crops which have great importance for their effective management in order to guarantee productive and sustainable agriculture [6]. The diagnosis of plant diseases is usually performed visually and may present flaws due to its laborious and subjective nature [7]. The study of Barbedo [19] suggests a methods of computer vision with artificial intelligence to automate the process of detection of diseases in plants. The automatic detection of diseases from images includes, among other factors, the determination of the most discriminative characteristics for the efficient recognition of the disease. The use of computer vision particularly deep learning in the field of agriculture only began to take place in the last couple of years, and to a rather limited extent. It was being utilized to identify diseases in rice [20], banana [21], avocado [22], grapes [23], coffee [24], abaca [7], and cassava [12].

2.3. Deep convolutional neural network and transfer learning

The accuracy of the network used to detect diseases relies mainly on the complexity and structure of the architecture [11]. Deep learning convolutional neural network has different architectures, each has different implementation of the idea of deep convolutional neural network [18]. One of the examples of deep convolutional network is Visual Geometry Group network architecture which is distinguished by its simplicity. It uses 3×3 convolutional layers stacked on top of one another in increasing depth with max pooling to reduce volume size. It has a deep of 16 and 19 weight layers [25]. Meanwhile, deep residual learning framework (ResNet) was developed to address degradation problem due to deeper networks. Instead of hoping each few stacked layers directly fit a desired underlying mapping, let these layers fit using a residual mapping [26]. Another solution to degradation problem due to deeper network is addressed by DenseNet architecture. This architecture simplifies the connectivity pattern and ensures the maximum information flow [27]. MobileNet, which is also a deep learning convolutional network architecture, is better suited to mobile and embedded vision applications with limited computational resources. When compared to a network with conventional convolutions of the same depth in the networks, this design employs depth wise separable convolutions, which greatly decreases the number of parameters, resulting in a light weight deep neural network [28]. Furthermore, Inception-v3 is a convolutional neural network architecture designed based on the Inception group that transports label information lower down the network using label smoothing, factorized convolutions, and an auxiliary classifier [29]. Xception architecture, on the other hand, is a version of inception architecture that uses depth wise separable convolutions to replace Inception modules [30].

Structure of the architectures is one of the main concerns because training a deep convolutional neural network is difficult to realize since it requires high computing power [12] and a large amount of data in order to attain better results [13]. The study of Jiang *et al.* [13], Ramcharan *et al.* [12], and Sagar and Dheeba [15] explores the use of transfer learning and deep learning optimizers in order to address the insufficient data problem and minimal time of training the model.

3. RESEARCH METHOD

3.1. Experimental setup

In conducting the experiment, capturing healthy and leaf spot infected peanut leaves in the sampling sites using a mobile camera was done first. The background of the image was also considered as part of the experiment. Images were cleaned, pre-processed, and augmented to eliminate duplication, improve the quality of the images, and introduce minimal distortion to the images which aids in reducing overfitting at the training stage. Cleaned images were considered as a dataset and were subjected to training.

During training, the dataset was divided into two groups: healthy and infected peanut leaves. Weights from ImageNet trained large dataset using VGG16, VGG 19, InceptionV3, MobileNet, DenseNet-169, Xception, InceptionResNetV2, and ResNet50 architectures were used for retraining. During retraining, deep learning optimizers such as stochastic gradient descent (SGD) with momentum, adaptive moment estimation (Adam), root mean square propagation (RMSProp), and adaptive gradient algorithm (Adagrad) trained on different learning rate were explored. To give an unbiased evaluation of a model retrained on the training dataset, the candidate model was used to predict the responses in the validation dataset. Using the test dataset, candidate retrained models were evaluated in order to assess their performance. Each candidate model was assessed based on its ability to distinguish between healthy and infected peanut leaves in photos. Figure 1 is the experimental set-up used in the study.

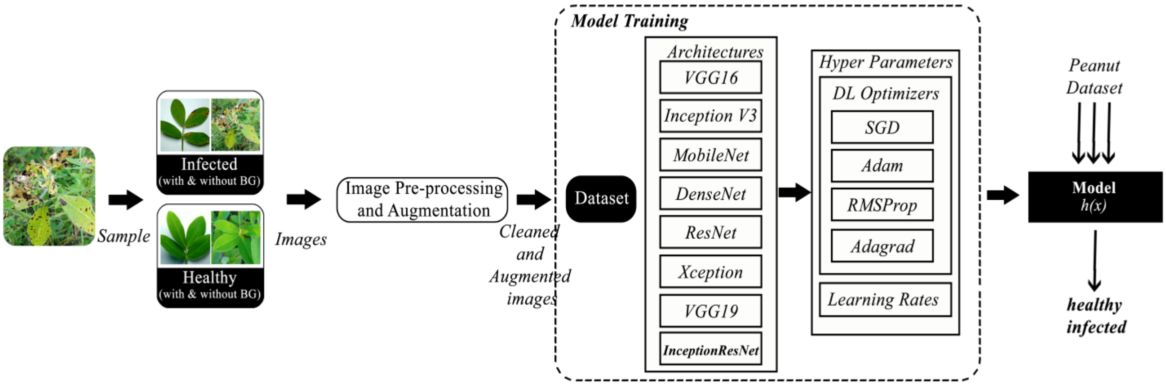

Figure 1. Experiment set-up

3.2. Data gathering

The sampling site of the study is in Liloy, Zamboanga del Norte. The camera used was RealMi 6i mobile phone with 48-megapixel back camera and 16-megapixel front camera. Upon the taking of images, camera was set to manual mode and positioned 0.25 meter above the leaves. In this study, isolation or background elimination was also considered [13]. Sample images of healthy leaves without background and with background is shown in Figures 2(a) to 2(d). A total of 1,000 images captured from the sampling site were validated by experts in plant disease.

(a) (b) (c) (d)

Figure 2. Sample images of (a) healthy leaves without background, (b) with background elimination, (c) leaf spot infected leaves without background, and (d) with background elimination

3.3. Data pre-processing

Before training, images were labeled based on two groups: healthy and infected leaves. Anchoring to the study of Mohanty *et al.* [10], the datasets were divided as follows: 600 images (60%) used for training, 100 images (10%) used for validation, and 100 images (10%) were used for testing. Table 1 is the distribution of actual samples based on different factors. Before feeding the images into the network, they were resized to 255×255 in order to reduce the training time [7]. Augmentation such as affine transformation was also applied in order to increase the dataset and apply slight distortion to the images to reduce over-fitting [6]. In this study, rescaling and pixel normalization were also applied.

Table 1. Distribution of actual samples based on different factors

Part		Type	Total Number of Images		Training 60%	Validation 20%	Test 20%
Leaves	Healthy	With Background	250 images	500 images	300 images	50 images	50 images
		Without Background	250 images				
	Infected	With Background	250 images	500 images	300 images	50 images	50 images
		Without Background	250 images				

3.4. Training of data using transfer learning approach

Transfer learning is based on the idea of reusing a previously trained model on a similar domain rather than retraining a new model from scratch to improve its performance. In this study, pre-trained VGG16, VGG 19, InceptionV3, MobileNet, DenseNet-169, Xception, InceptionResNetV2, and ResNet50 were used for training. The architecture is depicted in Figure 3 and begins with several data augmentation approaches. The images used for training and testing are converted to a 1D array and fed to the dense layer using the flatten layer. A dropout layer with a dropout rate of 0.7 and a sigmoid activation function was added for input classification. Adopting the study of Saleem *et al.* [16], this study used different deep learning optimizers such as stochastic gradient descent (SGD) with Momentum (beta=0.9) [31], adaptive moment estimation (Adam), Adagrad, and root mean square propagation (RMSProp) at different learning rates [16].

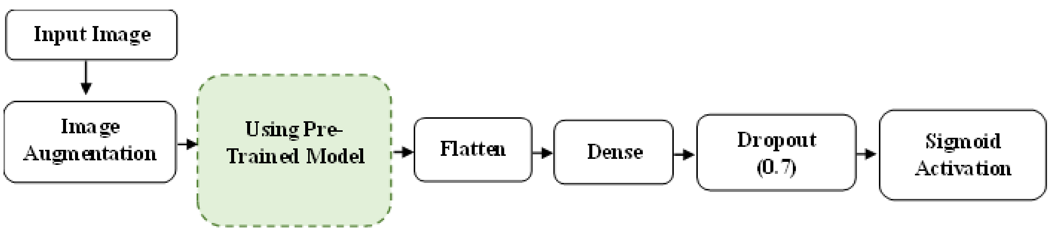

Figure 3. The transfer deep learning approach used in the study

3.5. Hardware and software

To train and test the model, python programming language was employed and coded using Jupyter Notebook. Python libraries such as pandas, NumPy, matplotlib.pyplot, math, sklearn, and Keras built on top of the tensor flow architecture [7] were utilized. Table 2 is the specification of the hardware used in the study.

Table 2. Hardware specification used in the study

Parts	Specification
Processor	Intel(R) Core(TM) i7-9700 CPU @ 3.00GHz
Memory (RAM)	8 gigabytes (GB)
Storage	1 Terabyte (TB)
Graphics	NVIDIA GeForce GTX 1080 Ti graphics card

3.6. Evaluation

The typical method for evaluating the performance of artificial neural networks is to divide data into three sets: training, validation, and test, and then train a neural network on the training set and use the test set for prediction. Because the testing set's actual outcomes and the model's projected outcomes are both known, the accuracy of the predictions can be measured. During the testing process, a confusion matrix was used, and the different models were evaluated on the basis of accuracy and precision, where the formula is shown in (1) and (2), respectively. Accuracy is defined as how often the classifier is correct, while precision is the proportions of positive and negative results that are true positive and true negative results. It answers the idea that when the classifier predicts yes, how often is it correct.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Average or mean from complete training was considered in this study [7].

4. RESULTS AND DISCUSSION

The goal of this study is to create models that will identify the presence of disease and healthy leaves. Explore the use of transfer learning algorithm, isolation or background elimination, and deep learning optimizers considering the limited data. The succeeding subsections elaborate the results during the training and evaluation process.

4.1. Training

In this research, weights trained using 10,000+ images from ImageNet were obtained and utilized. Prior model training to obtain data visualization was performed to assess the performance of the models trained using different deep learning optimizers. The assessment was done since this research only utilized small and utterly different dataset from the dataset being used by the pre-trained model.

In this study, the researcher decided to train the model over 100 epochs. The reason to train each model over 100 epochs is for the researcher to babysit the training process and to identify which stage of the training process the accuracy and loss start to saddle and to what extent. A saddle point is when the gradient reaches a plateau, and the training loss becomes harder to improve.

4.2. Evaluation

During testing, the accuracy and precision of the various architectures trained using different deep learning optimizers were evaluated. The results were tallied and the average or mean of the 100 epochs training was taken into account. The accuracy and precision are shown in section 4.2.1 and 4.2.2.

4.2.1. Accuracy

The performance of the different pre-trained deep CNN architectures when trained using different deep learning optimizers in terms of accuracy is illustrated in Figure 4. The research revealed that 6 out of 8 architectures used in the study achieved an accuracy of 90% and above. On the other hand, SGD with momentum, Adam and RMSProp deep learning optimizers achieved the top 1, top 2, and top 3 in terms of accuracy in most of the pre-trained deep CNN architectures. In general, DenseNet-169 trained using SGD with momentum, Adam, and RMSProp attained the highest accuracy among pre-trained deep CNN architectures used in the study.

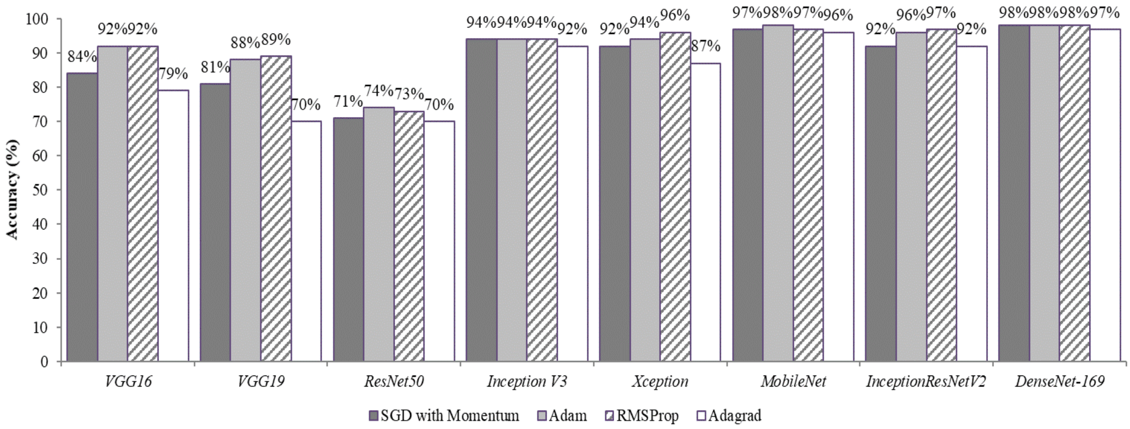

Figure 4. The accuracy of several deep CNN architectures when trained with different deep learning optimizers

4.2.2. Precision

The performance of the different pre-trained deep CNN architectures when trained using different deep learning optimizers in terms of precision is illustrated in Figure 5. The research revealed that 6 of the 8 architectures used in the study had precision of 90% or higher. Meanwhile, SGD with momentum, Adam and RMSProp deep learning optimizers achieved the top 1, top 2, and top 3 in terms of precision in most of the pre-trained deep CNN architectures. In general, DenseNet-169 trained using RMSProp attained the highest accuracy among pre-trained deep CNN architectures used in the study.

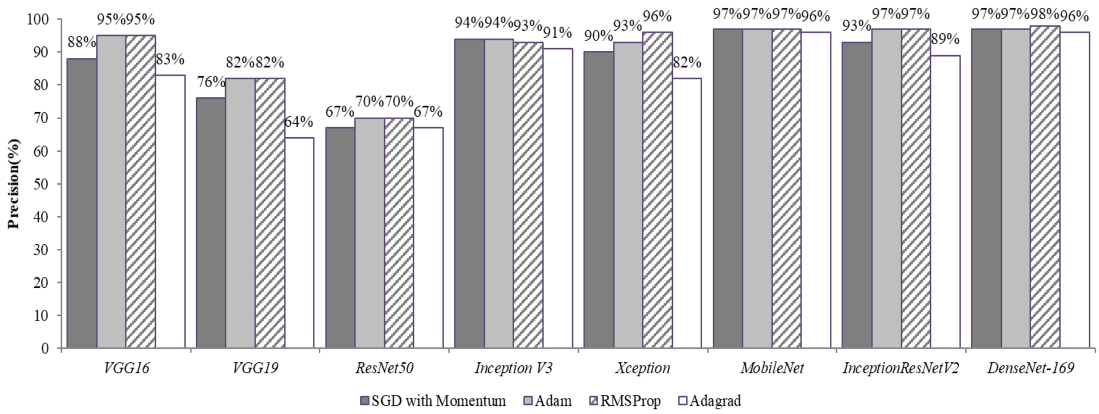

Figure 5. The precision of various architectures trained using various deep learning optimizers

5. CONCLUSION AND RECOMMENDATION

One of the factors associated with the low production of peanut or groundnut is a disease, particularly the early leaf spot and late leaf spot which are common in the Philippines due to warm and humid climate. Studies suggest that early detection and appropriate monitoring are the ways that would possibly prevent and control the disease. In computer vision deep learning, the deep convolutional neural network is becoming the preferred method in disease identification and classification due to its impressive performance. The study explores the use of transfer learning algorithm, isolation or background elimination, and deep learning optimizers in order to address the insufficient data problem in creating a model that can identify leaf spot disease.

Using pre-trained VGG16, VGG19, InceptionV3, MobileNet, DenseNet-169, Xception, InceptionResNetV2, and ResNet50 architectures retrained using deep learning optimizers, the result shows that DenseNet-169 trained using SGD with momentum, Adam, and RMSProp attained the highest accuracy. In contrast, DenseNet-169 trained using RMSProp achieved the highest precision among pre-trained deep CNN architectures as used in the study.

Given the findings, the use of a pre-trained deep convolutional neural network or transfer learning algorithm, pre-processing techniques, and deep learning optimizers can alleviate problem in data insufficiency and attain better accuracy and precession results. In addition, this study could be beneficial in agricultural automation, particularly in creating robotic systems and disease identification systems that can identify or classify healthy and infected peanut or groundnut plants. Further, it is also recommended to increase not only the number of training images, but also the number of classes of the different commercially important Philippine crops in particular. Follow up study will also be recommended to further evaluate the models when it will be implemented in terms of effectiveness and price in compare with other classification algorithms.

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