Identification System Via Deep Transfer Learning of Philippine Indigenous Plants

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Abstract - **Plant classification is a task that is of great importance to effectively study a plant. It is done by taxonomists, botanists, and other practitioners that are in the field of agriculture, biodiversity protection, wildlife conservation and so on. Plantita is a website application that intends to accelerate classification of Philippine indigenous plants through utilization of a MobileNetV3Large convolutional neural network (CNN) architecture, a deep learning technology. There were 1200 images collected for the 10 indigenous plants which were split into training set, validation set, and test set. The images were augmented, trained, and tested with the CNN model that underwent a different fine-tuning process which resulted to choosing a model with 20% dropout to reduce overfitting and achieved an overall accuracy of 90%.**

Keywords – Plant classification, deep learning, transfer learning, Philippine indigenous plant, augmented reality

I. INTRODUCTION

Identification and classification of plants is a complex undertaking, even for practiced taxonomists. Manual categorization is time-consuming, expensive, cumbersome, and necessarily involves experienced experts, who are frequently limited available [1]. This phenomenon remains to be a problem across the globe as it hinders the acceleration of distribution of data and information to improve public awareness with regards to plants. The lack of information decreases the support for conservation of plants and saving biodiversity. The country of the Philippines has abundant flora, and indigenous plants are one of many that the Philippines has to offer. However, many citizens are not aware of the existence and significance of indigenous plants. A fraction of population may have knowledge about these plants, but most of the population are uninformed of their presence. Thus, a technology that enables classification of plant species and can be useful not only to the experts, but to general public as well. The recorded flora in the Philippines as of 2002 by the Department of Environment and Natural Resources (DENR) is at minimum of 14,000 species [2]. Since the country's flora is broad and diverse, the study is only limited to ten (10) indigenous plant species namely, Anahaw, Bagawak-Morado, Bignay, Copeland's Pitcher, Kalingag, Katmon, Kris Plant, Payau, Tangisang-Bayawak, Tayabak.

Many mobile applications for plant identification are already in the digital distribution service platforms such as Google Play Store and Apple App Store. A few of these applications are iNaturalist, and LeafSnap. iNaturalist is a website and a mobile application where naturalists can use the site to map and share photographic observations of biological diversity from around the world. Each observation includes a date, location, images, and labels that include the species name depicted in the photograph [3]. A total of 250 countries are the coverage area of iNaturalist, Philippines is included among these countries. However, the application database is heavily biased towards United States, United Kingdom, Australia, South Africa, and New Zealand [4]. Only few plant identification applications have a database about the Philippines' indigenous plants because of the fact that the existing applications are predominantly created by foreign researchers for foreign countries such as United States, and Oceana. Thus, information and education regarding Philippine indigenous plants is less accessible compared to plants' information across other countries.

To overcome the aforementioned difficulties, we created a plant classification system with implementation of transfer learning process with Convolutional Neural Network models. The CNN models that were used were VGG-16, Xception, VGG19, InceptionV3, and MobileNetV3Large. The most preferred neural network for image classification is Convolutional Neural Network (CNN) due to its capability to train and predict in abstract level where the basis is a linear algebra. CNN comprises several layers, the initial layer, output layer, and numerous hidden layers. Each layer involves a unique set of image set characteristics. Initial layer learns the basic characteristics such as bright and dark areas, edges, and shapes in an image, plant image as an example. The next layers recognize the image relation to the shapes and objects. Essentially, CNN matches parts of an image rather than the entire image, dividing the image classification process into smaller features [5].

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II. RELATED WORKS

In a study conducted on Classification of Plant Seedlings pre-trained convolutional neural network models such as AlexNet, GoogLeNet, and ResNet50 are used in performing image classification of different data. Transfer learning is applied to these models to lessen the training time. ResNet50 gave the most favorable results with an accuracy rate of 90% in classifying the datasets [7].

An app called LeafSnap PH is used to identify leaves of Philippine plants in general. Support Vector Machine was used for the deep learning process, and conversion from Red, Green, Blue (RGB) to Hue, Saturation, Value (HSV) were applied to raw images of the leaves of the plants, as feature extraction of the leaves is highly important when identifying [8]

A group of researchers utilized 31 transfer learning in fine tuning CNN models such as AlexNet, VGG16, VGG19, and Inception-v3. From these methods, they were able to conclude that Inception-v3 was the suitable architecture for image classification through transfer learning, [5]. Meanwhile for classifying images VGG19 had the highest performance output [9].

Another study further supported these claims with findings of high accuracy rates on models such as Xception with 92.5%, VGG16 with 92.1%, VGG19 with 91.42%, and Inception-v3 with 88% [10]

A study done on classification of garbage which utilized MobileNet obtained an accuracy of 87.2% [11]. MobileNet is a model developed originally from VGG architecture that has three versions iterating from MobileNetV1, MobileNetV2, and the latest MobileNetV3. To increase the efficiency and accuracy the new MobileNetV3 drops expensive layers and using h-swish nonlinearity function instead of ReLU [12].

III. MATERIALS AND METHOD

A. *Dataset*

In this study, the dataset used has a total count of 1200 images. The dataset was divided into three sets: 800 images are in the training set, 200 images in the testing set and 200 images in the validation set. The images were resized to 224 x 224 pixels for the VGG 16, VGG 19, and MobileNetV3 CNN models, while for the Xception CNN model, images were resized to 150x150.

TABLE I
Philippine Indigenous Plants and their Scientific Names

Common Name	**Scientific Name**
Anahaw	*Saribus rotundifoluis*
Bagawak Morado	*Clerodendrum quadriloculare*
Bignay	*Antidesma bunius*
Copeland's Pitcher	*Nepenthes copelandii*
Kalingag	*Cinnamomum mercadoi*
Kris Plant	*Alocasia sanderiana*
Katmon	*Dillenia philippinensis*
Payau	*Homalomena philippinensis*
Tayabak	*Strongylodon macrobotrys*
Tangisang Bayawak	*Ficus variegate*

B. *Data Augmentation*

To further increase the diversity of datasets, the image shall undergo data augmentation. The image augmentation methods used are as follows:

- Flipping – The images were flipped horizontally and vertically.
- Zoom – The images were magnified randomly 10% times of the original images
- Rotating – The images were rotated randomly 10 % of the original position of the image

C. *Models and Implementation*

The Transfer Learning process was implemented by utilizing four CNN models which were trained with a large dataset and applying its knowledge to the classification task at hand. The pre-processed and augmented data sets are fed into the Convolutional Neural Network (CNN) models.

- VGG-16-comprises of 16 layers, is a CNN architecture that comprises of Convolutional layers, Max Pooling Layers, Fully Connected layers, and a softmax layer.
- VGG-19 – uses the ImageNet database to train itself on over a million images. VGG 19 comprises of 19 layers with 16 of it as Convolutional Layers and 3 are Fully Connected Layers.
- Xception - Extreme Inception is an enhanced architecture of the Deep Neural Network of Inception. The Xception architecture has 36 convolutional layers which are structured into 14 modules.
- MobileNetV3-Large- is a CNN architecture designed for mobile phone CPUs. MobileNetV3-Large is an iteration and improvement from previous MobileNet versions and is designed for high resource CPUs of mobile phone. Which utilizes network architecture search (NAS) and NetAdapt Algorithm.

D. *Optimization and fine-tuning of CNN models*

To identify the optimum CNN model, variations of the architecture of the models were tried by changing the structure of its classifier, adding a fine-tuning process, and adding regularization techniques such as dropout to reduce overfitting.

- Fully Connected Layer – first classifier used on top of pre-trained CNN model where all input nodes of a layer are connected to every node on the next layer.
- Global Average Pooling- second classifier utilized that reduces parameters of the model and generates one feature map for each class.

III. RESULTS AND DISCUSSION

A. *Training and Validation Accuracies*

The pre-trained convolutional neural networks are evaluated by analyzing its training accuracy and validation accuracy. Validation accuracy will be compared to the training accuracy to assess if the model is either overfitting or underfitting.

The graphs of Figure 1, Figure 2, Figure 3, and Figure 4. shows the training accuracy vs training loss and validation accuracy and validation loss for Fully Connected Layer with 20% Dropout and Fine Tuning. The blue line shows the Training Accuracy and Training Loss, while the orange line shows the Validation Accuracy and Validation Loss.

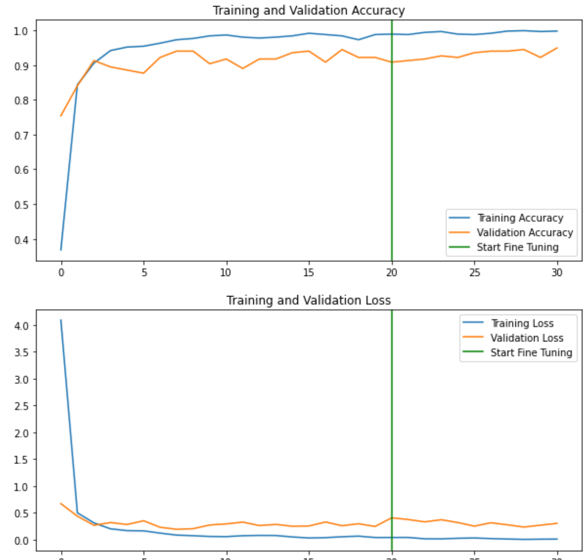

Figure 1.VGG-16 FCL with 20% Dropout and Fine-Tuning

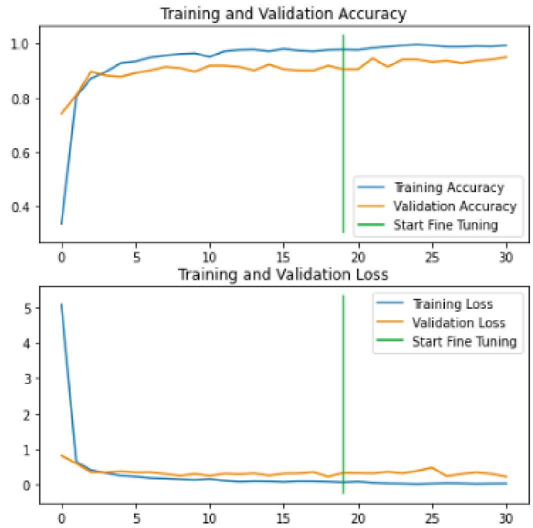

Figure 2.VGG-19 FCL with 20% Dropout and Fine-Tuning

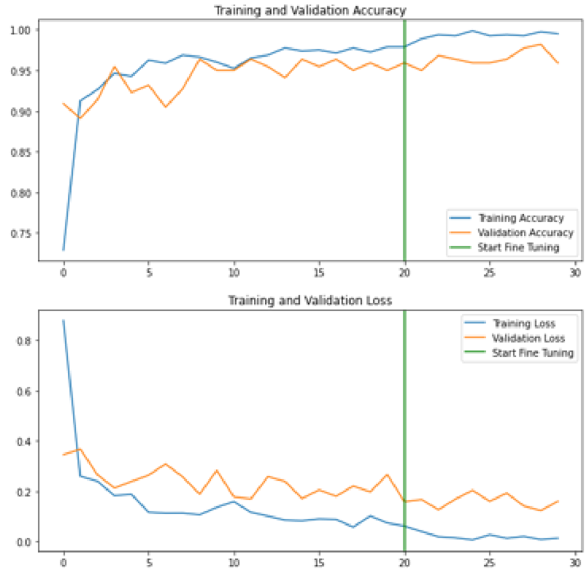

Figure 1. Xception FCL with 20% Dropout and Fine-Tuning

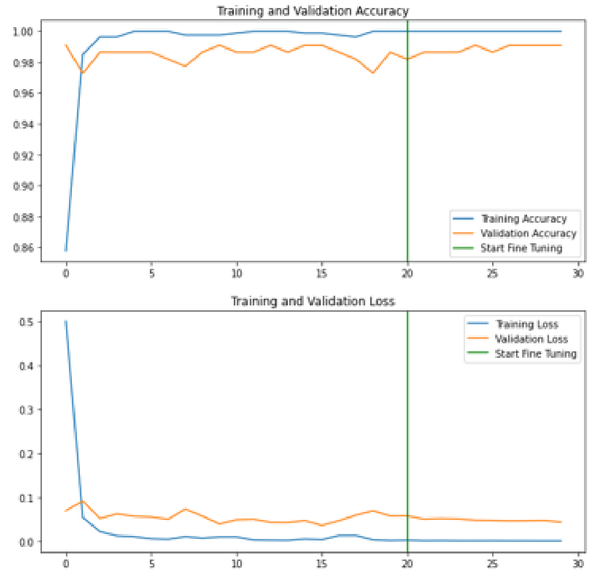

Figure 2. MobileNetV3-Large FCL with 20% Dropout and Fine-Tuning

While Table II shows the comparison of the Training Accuracy and Validation Accuracy of the four Convolutional Neural Network (CNN) Models. With VGG-16 having 99.87 % Training Accuracy and 95 % Validation Accuracy, VGG-19 with 99.37 % Training Accuracy and 95% Validation Accuracy, Xception having 99.50 % Training Accuracy and 95.91 % Validation Accuracy, and MobileNetV3-Large with 100 % Training Accuracy and 99.09 % Validation Accuracy.

TABLE II
Training and Validation Accuracies of Fully Connected Layer with 20% Dropout and Fine-Tuning

CNN Models with Fine- Tuning	**Training Accuracy**	**Validation Accuracy**
VGG-16	99.87 %	95 %
VGG-19	99.37 %	95 %
Xception	99.50	95.91 %
MobileNetV3-Large	100 %	99.09 %

Table III shows the comparison of the Training Accuracy and Validation Accuracy of the four Convolutional Neural Network (CNN) Models for the FCL with 50% Dropout and Fine-Tuning

TABLE III
Training and Validation Accuracies of Fully Connected Layer with 50% Dropout and Fine-Tuning

CNN Models with Fine- Tuning	Training Accuracy	Validation Accuracy
VGG-16	99 %	93.64 %
VGG-19	98.5%	94.55%
Xception	99.25%	96.82%
MobileNetV3-Large	100 %	99.09 %

Table IV and Table V shows the comparison of the Training Accuracy and Validation Accuracy of the four Convolutional Neural Network (CNN) Models for the Global Average Pooling with 20% Dropout with Fine Tuning and 50% Dropout with Fine Tuning respectively.

TABLE IV
Training and Validation Accuracies of Global Average Pooling with 20% Dropout with Fine Tuning

CNN Models with Fine- Tuning	Training Accuracy	Validation Accuracy
VGG-16	98.62 %	95.45 %
VGG-19	98.75%	93.18%
Xception	99 %	98.64%
MobileNetV3-Large	82.44 %	83.17%

TABLE V
Training and Validation Accuracies of Global Average Pooling with 50% Dropout with Fine Tuning

CNN Models with Fine- Tuning	Training Accuracy	Validation Accuracy
VGG-16	98.25 %	96.36 %
VGG-19	97.12%	91.36%
Xception	97.12 %	99.55%
MobileNetV3-Large	99.62 %	99.09%

Overall, the CNN models with Fully Connected Layer architecture, 20% Dropout, and Fine-Tuned generally resulted with the most optimum performance for the classification task, with MobileNetV3-Large having the highest accuracy for both Training and Validation.

V. CONCLUSION

The four Convolutional Neural Network models with different architecture were successfully trained and tested. Their results are compared and evaluated to select the architecture that performs the best for the classification of Philippine indigenous plants.

MobileNetV3Large with fully connected layer classifier, a dropout of 20% and is fine-tuned has the highest performance on identifying Philippine indigenous plants among the pre-trained CNN models.

The findings on the evaluation of the Plantita website application suggests that the use of Convolutional Neural Network, and Augmented Reality experience as an education tool to inform the general public regarding Philippine indigenous plants has been successful. The Filipino foresters who has evaluated the website also commends its promising utilization for other purposes in the future including but not limited to managing and mapping of the plants on protected areas.

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