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ANGIOSPERM SPECIES CLASSIFICATION USING TRANSFER LEARNING IN CONVOLUTIONAL NEURAL NETWORKS

Jessica S. Velasco[1], Jannabelle J. Tiguara[1], Abhrei Mikael D. Torres[1], Marinel B. Valencia[1], Jovencio V. Merin[2] and Jomer V. Catipon[1]
[1]Department of Electronics Engineering College of Engineering, Technological University of the Philippines, Manila, Philippines
[2]Department of Electrical Engineering, College of Engineering, Technological University of the Philippines, Manila, Philippines
E-Mail: jessica_velasco@tup.edu.ph

ABSTRACT

The species composition provides the fundamental individual biological characteristics of an environment and ecosystems. The ability to identify species of individual plants or trees over an assessment plot and a forest stand is necessary for automatic mapping of plant distribution, biological diversity, stand structure, and even for diagnosing the dynamics of a forest stand. The advantage of developing plant mapping techniques utilizing image classification is the ability to identify signs of climate change based on plant phenology. Due to the large number of sequential layers and input data, deep learning takes a long time to train. Due to its capacity to do parallel processing, a powerful computer with a Graphic Processing Unit is the best choice for the training process. To classify angiosperm species, this study used photos from the University of Oxford dataset to represent 10 different angiosperm or flowering plant species. The 800 images used for the training and testing of various convolutional network models are made up of angiosperm species like bluebell, cowslip, crocus, daisy, dandelion, fritillary, iris, snowdrop, sunflower, and windflower. This study employed pre-trained weights from several convolutional neural network models, such as DenseNet 201, InceptionV3, MobileNet, ResNet152V2, ResNet50, and Xception, to classify the angiosperm species. The ResNet50 model had the lowest accuracy, 91.87%, while the Xception model had the greatest accuracy, 97.5%.

Keywords: angiosperm classification, deep learning, convolutional neural networks, transfer learning, python.

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1. INTRODUCTION

More than any other group of plants, angiosperms predominate on Earth's surface and in its vegetation, especially in terrestrial areas. The primary source of food for animals, including humans and birds, is angiosperms. Additionally, the most economically significant category of green plants is the group of flowering plants, which are a source of goods including medicines, fiber, lumber, ornamentals, and other commercial goods [1]. Basic individual biological characteristics of a landscape and a forest ecosystem are provided by species composition. The automatic mapping of plant distribution, biological diversity, stand structure, and even for diagnosing the dynamics of a forest stand all depend on the capacity to identify species of individual plants or trees over an inventory plot and a forest stand. The development of plant mapping methods has the advantage of detecting climate change signals based on plant phenology [2].

Numerous image-based techniques for classifying plant species have been suggested in recent decades. Most techniques made use of red, green, and blue (RGB) imaging components and created unique characteristics to categorize the plant photos using machine learning algorithms. Instead of live-crown pictures, those efforts mostly concentrated on single-leaf image analysis. However, due to the restricted spectrum information of RGB imagery, they were unable to manage scenarios that had leaves that were identical in appearance without considering the extra elements of the color and spatial pattern [3]. In that sense, this paper proposes a method for classifying plant images using deep learning approaches.

Deep learning has become a popular data processing technique in recent years due to advancements in hardware technology [4]. Convolutional neural networks (CNN) are the most well-known and used Deep Learning techniques in the computer vision and image processing sectors [5]. In contrast to Machine Learning, CNN may combine the classifier, feature learning, and feature derivation into a unified architecture. If there is enough training data, several studies have shown that employing CNN algorithms may result in much greater accuracy than using standard ML ones. CNN can automatically learn the most discriminative, multi-scale, and objective characteristics from unprocessed data without the interference of human subjectivity, which is the primary cause. Additionally, the spatial link between overlapping patterns and leaf arrangement, or phyllotaxy, may be determined. To put it another way, different spatial properties of items of interest that are shown in a VHSR picture may be processed by reducing the signals from background materials and afterwards identified based on the spatial pattern in spectra. With the use of plant morphological characteristics such as leaf size, color, contour, venation, and even phyllotaxy, we can identify different plant species in a method that is quite similar to that of phytologists. Due to their specific visual properties, these

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conditions are suitable for classification utilizing artificial intelligence and underlying deep learning approaches. Angiosperm species that can potentially be identified by image recognition technologies are buttercup, colt's foot, daffodil, daisy, dandelion, fritillary, iris, pansy, sunflower, windflower, snowdrop, lily valley, bluebell, crocus, tiger lily, tulip, and cowslip.

The researchers suggest using photos gathered from reputable and openly accessible websites like GitHub to visually infer the angiosperm species and classifying each image into the appropriate group using transfer learning models.

2. CONCEPTUAL LITERATURE

A. Transfer Learning

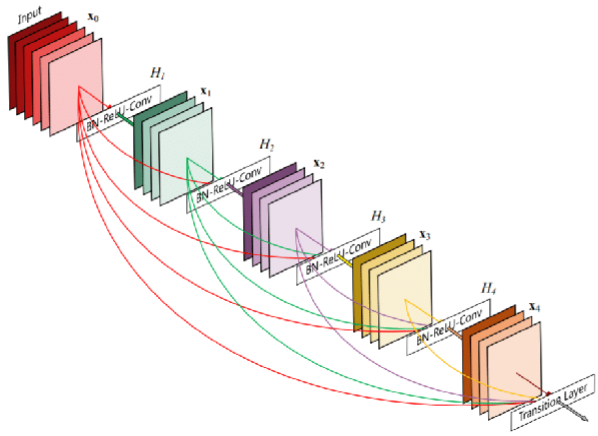
Although most machine learning algorithms are created to handle tasks, the creation of algorithms that support transfer learning is a subject of constant attention in the machine learning community. Transfer learning is the process of learning a new task more effectively by applying what has already been learned about a related one [6]. This is a machine learning technique where a model developed for a task is reused as the starting point for a model on a second task. Pre-trained models are used as the starting point on computer vision and natural language processing tasks given the vast compute and time resources required to develop neural network models and from the enormous jumps in skill that they provide on related problems [7].

B. Keras Platform

A high-level neural network API called Keras was created using Python, is capable of running alongside applications like TensorFlow, CNTK, or Theano. Best practices for lowering cognitive load are followed by Keras, which provides consistent & simple APIs, reduces the amount of user activities necessary for typical use cases, and gives clear & actionable error signals. Additionally, it contains a wealth of development instructions and documentation. With support for each stage of the machine learning workflow, including data management, hyperparameter training, and deployment options, Keras is a key component of the intricately interconnected Tensor Flow 2 ecosystem [8].

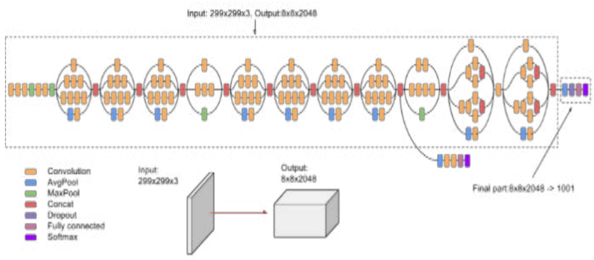
C. DenseNet 201

The Dense Convolutional Network (DenseNet) feeds forward connections between every layer. They reduce the number of parameters significantly, enhance feature propagation, increase feature reuse, and solve the vanishing-gradient problem. DenseNet is based on the idea that convolutional networks may be trained to be significantly deeper, more precise, and more effective if the connections between the layers near the input and the layers near the output are shorter [9]. DenseNet-201 is a convolutional neural network that is 201 layers deep. The ImageNet database contains a pretrained version of the network that has been trained on more than a million pictures [10]. The pretrained network can categorize photos into 1000 different item categories, including several animals, a keyboard, a mouse, and a pencil.



D. Inception V3

On the ImageNet dataset, it has been demonstrated that the picture recognition model Inception v3 can achieve higher than 78.1% accuracy. The model is the result of several concepts that have been established by various scholars throughout the years. It is based on the original paper: "Rethinking the Inception Architecture for Computer Vision" by Szegedy, et al. Convolutions, average pooling, max pooling, concatenations, dropouts, and fully connected layers are some of the symmetric and asymmetric building components that make up the model itself. The model makes considerable use of batch normalization, which is also applied to the activation inputs [11].



E. MobileNet

Convolutional neural networks, such as MobileNet, are specialized for use in embedded and mobile vision applications. They are based on a simplified design that uses depth-wise separable convolutions to create compact deep neural networks with reduced latency for embedded and mobile devices. Convolution layers that are depth-wise separable are the foundation of MobileNet [12]. A depthwise convolution and a pointwise convolution make up each depthwise separable convolution layer. A MobileNet contains 28 layers if

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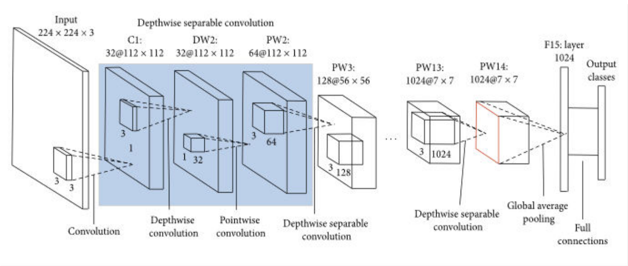
depth-wise and pointwise convolutions are counted as separate layers. A conventional MobileNet has 4.2 million parameters, which may be further decreased by properly setting the width multiplier hyperparameter [13].

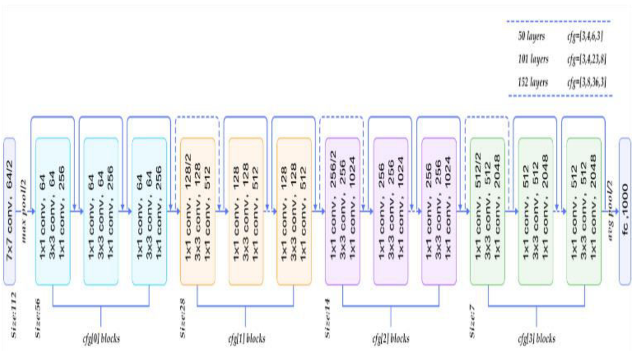


F. ResNet152V2

Instead of directly learning the signal representation, the 152 convolutional layers of the Resnet152v2 model process the input picture by learning the residual representation functions. ResNet152V2 provides the skip connection (also known as a shortcut connection) to seamlessly fit the input from one layer to the next [14].

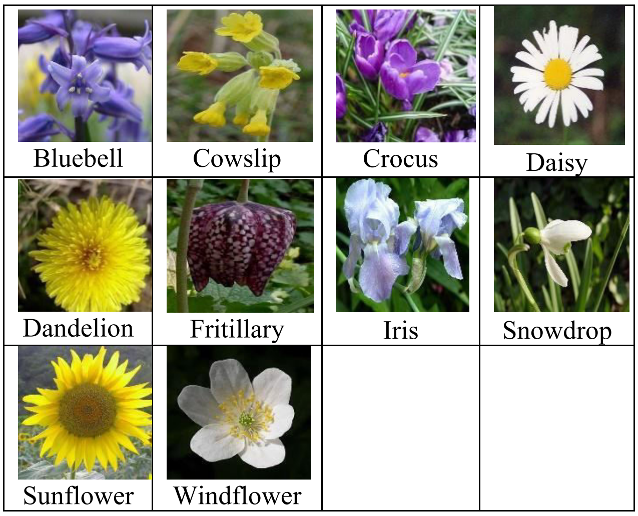
G. ResNet50

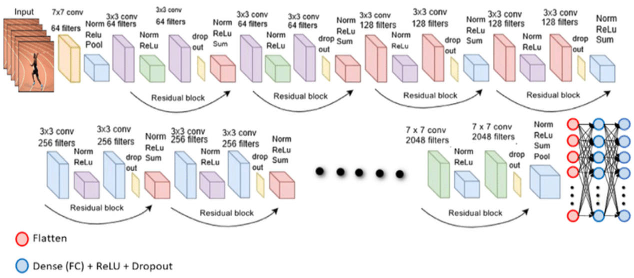
ResNet-50 is a pretrained Deep Learning model for image classification of the Convolutional Neural Network (CNN, or ConvNet), which is a class of deep neural networks, most commonly applied to analyzing visual imagery. It has 50 layers of convolutional neural network. The model also boasts over 23 million trainable parameters, indicating a deep architecture that improves picture identification. There are 5 phases in the ResNet-50 model, each having a residual block. There are 3 layers in each residual block, each with 1*1 and 3*3 convolutions. The idea of leftover blocks is rather straightforward [15].



H. Xception

Xception is a 71-layer convolutional neural network. The ImageNet database contains a pretrained version of the network that has been trained on more than a million images. The pretrained network can categorize photos into 1000 different item categories, including several animals, a keyboard, a mouse, and a pencil. The network has therefore acquired rich feature representations for a variety of images [16].





3. METHODOLOGY

A. Dataset

The images needed for the development of this project, which is in the Oxford 17 Flowers Dataset, are gathered at https://www.kaggle.com/datasets/datajameson/. The researchers reduced the classes from 17 to 10 classes, which consist of bluebell, cowslip, crocus, daisy, dandelion, fritillary, iris, snowdrop, sunflower, and windflower. A selection of images of angiosperm or flowering plant species is shown in Figure-1.

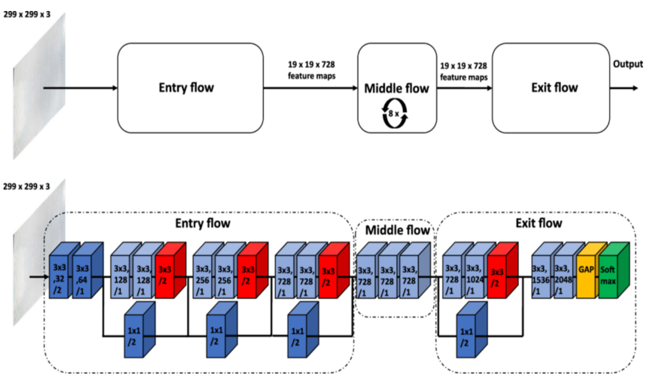


Figure-1. Sample images of dataset.

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There are 10 categories of angiosperm species in the dataset, and each image has a .jpeg extension. The poses and lighting in the images vary significantly, and there is also substantial intra-class diversity as well as a high degree of resemblance across other unique groups. The fact that there are only 80 photos in total for each class makes this dataset much more difficult. Consequently, there are 800 images in total, with Figure-1 showing their breakdown.

Table-1. Dataset.

Angiosperm Specie	Number of Images	Train Data	Test Data	Validation Data
Bluebell	80	64	16	16
Cowslip	80	64	16	16
Crocus	80	64	16	16
Daisy	80	64	16	16
Dandelion	80	64	16	16
Fritillary	80	64	16	16
Iris	80	64	16	16
Snowdrop	80	64	16	16
Sunflower	80	64	16	16
Windflower	80	64	16	16
Total	800	640	160	160

The dataset is divided into 80% for training and 20% for testing. The test data or the train data are both used to gather the validation data. The train data, as indicated in Table-1, consisted of 640 images, while the test data, together with the number of validation data, consisted of 160 images.

B. Experiment

The system will be coded on the Keras platform with a Tensorflow backend. To run the Python and run the programs in this project to generate the software, Google Colab, which is Google's version of PyCharm, will be utilized. In particular, the following 17 angiosperm species may be detected by the system: buttercup, colt's foot, daffodil, daisy, dandelion, fritillary, iris, pansy, sunflower, windflower, snowdrop, lily valley, bluebell, crocus, tiger lily, tulip, and cowslip. This is accomplished using convolutional neural network transfer learning models like DenseNet201, Inception V3, MobileNet, RenseNet152V2, RenseNet50 and Xception.

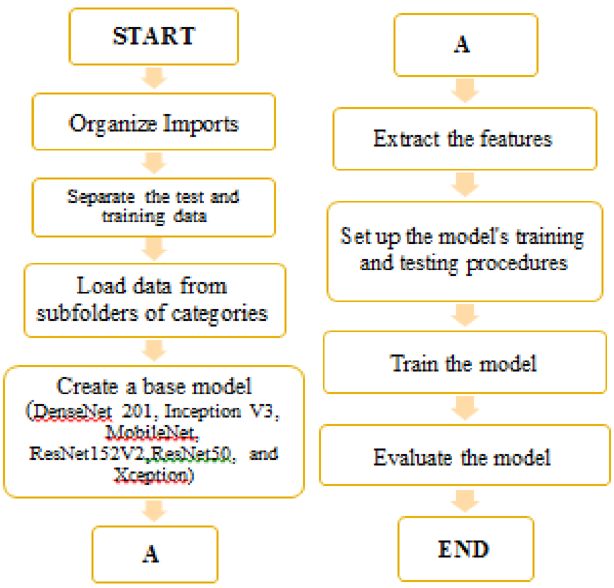

Figure-2. Program flowchart of the Python Code.

The program begins by arranging imports such as numpy, keras, scikit-learn, and matplotlib. The dataset should then be configured into several folders to separate the training and testing data (training, testing, and validation). The third step is to load images of angiosperm species from category subfolders. Following that, build a basic model using several pretrained convolutional neural networks. Then, preprocess the data to get the features; the tools in Keras can handle this automatically. The training

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and testing of the model must then be configured to be trained using the Adam optimizer. To determine which architecture is optimal for classifying angiosperm species, different systems will be assessed and compared based on model accuracy, confusion matrix, loading time, and weight size after training.

The size of the input picture varies for each model using pretrained convolutional networks. The input picture has the same width, height, and number of channels as the output image. The fixed size of the input picture for each model is displayed in Table-2.

Table-2. Input for each model.

Model	Input Image
DenseNet201	224x224x3
InceptionV3	299x299x3
MobileNet	224x224x3
RenseNet152V2	224x224x3
RenseNet50	224x224x3
Xception	299x299x3

4. RESULTS

Confusion matrix, loading time, accuracy, and weight size were taken into consideration while comparing and evaluating each pre-trained convolutional neural network's performance in classifying angiosperm species.

A. Confusion Matrices

The confusion matrices for the 10 categories of angiosperm species are displayed in Figures 3-8. Confusion matrix, also known as a matching matrix, in which the column denotes the actual class and the row denotes a predicted class. This demonstrates the commonality in misclassification across several convolutional neural networks.

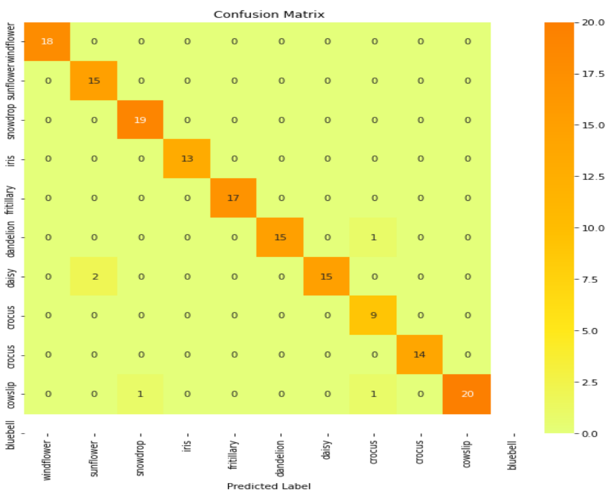

Figure-3. DenseNet201 confusion matrix.

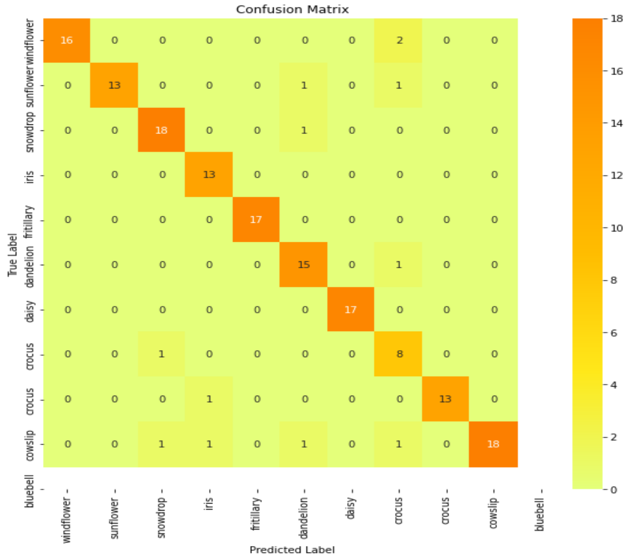

Figure-4. Inception V3 confusion matrix.

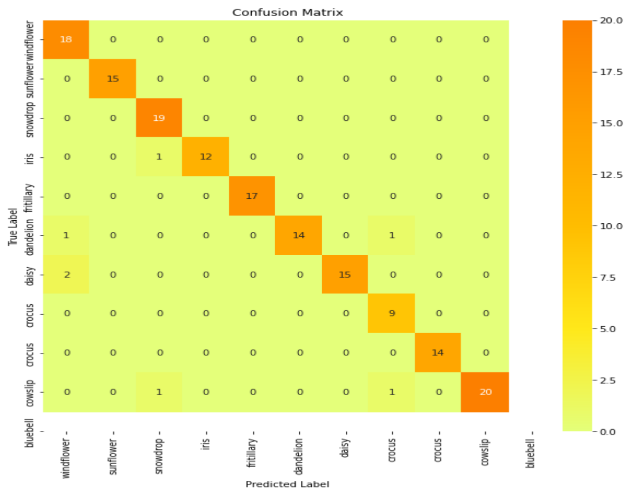

Figure-5. MobileNet confusion matrix.

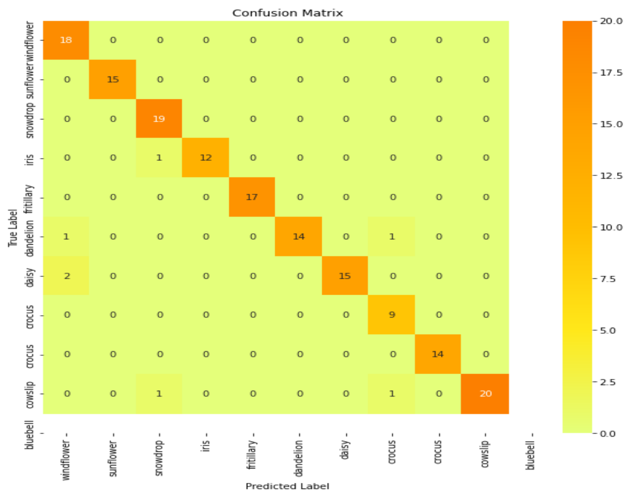

Figure-6. ResNet152V2 confusion matrix.

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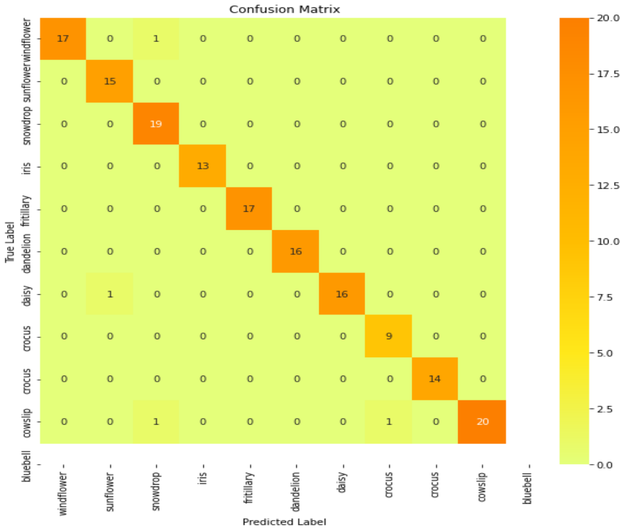

Figure-7. ResNet50 confusion matrix.

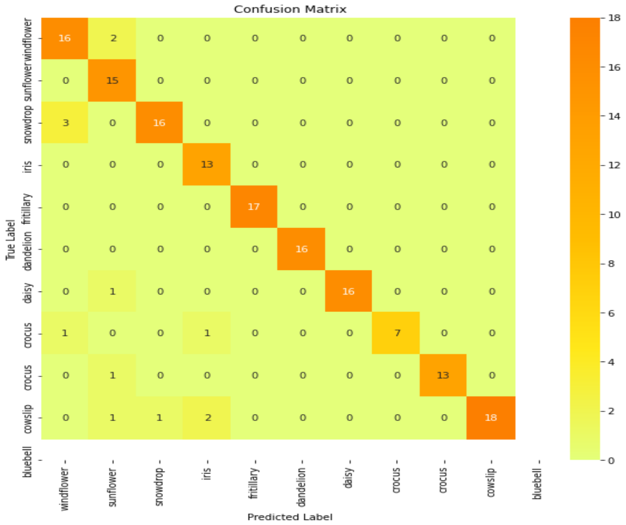

Figure-8. Xception confusion matrix.

B. Weight Size, Loading Time and Accuracy

The Xception model, which has an accuracy of 97.5%, a weight of 87.6 MB, and a loading time of five (5) seconds, is the best-performing model. Among the models, it provides the highest accuracy. However, at 16.8 MB, MobileNet is smaller in terms of weight, and with a loading time of one (1) second, the Inception V3 and ResNet 50 provided the quickest loading time.

Table-3. Evaluation of each model by its weight size, the loading time and accuracy.

Model	Weight Size	Loading Time (seconds)	Accuracy (Percent)
DenseNet 201	78.7 MB	5	96.87
InceptionV3	91.7 MB	1	92.50
MobileNet	16.8 MB	2	94.99
ResNet152V2	232 MB	2	95.62
ResNet50	98.2 MB	1	91.87
Xception	87.6 MB	5	97.5

C. Accuracy and Loss Graph

The performance of the algorithm is evaluated using an understandable accuracy metric. A model's accuracy is often assessed after the model's input parameters and is expressed as a percentage. It measures how well your model's forecast matches the actual data. The number of accurate predictions obtained is the accuracy score. Meanwhile, an algorithm for machine learning is optimized using a loss function, which is generated on training and validation data and is interpreted depending on how well the model performs in these two sets. In training or validation sets, it is the total number of mistakes produced for each sample. A model's loss value indicates how well or poorly it performs after each optimization cycle. Figures 9-14 show the accuracy and loss graph for the 10 categories of angiosperm species.

5. CONCLUSIONS

The models utilized in this study were still able to provide a substantial outcome in the accuracy of the machine learning tools even with 10 classes or categories. There are classes with many variants of photos within the class and close similarities to other classes, while having huge changes in scale, pose, and light. This dataset is significantly more challenging because there are only 80 photos for each class. In the train dataset, only 64 photos, or 80% of the original 80 images per category, were used in this project, and the remaining 16 images were used in

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the test dataset. As a result, the Xception model, which has an accuracy of 97.5 %, a weight of 87.6 MB, and a loading time of five (5) seconds, is the best-performing model out of the six used in this project. It offers the highest accuracy of all the models. The Inception V3 and ResNet 50 delivered the fastest loading times, with a loading time of one (1) second, whereas MobileNet is lighter in terms of size at 16.8 MB.

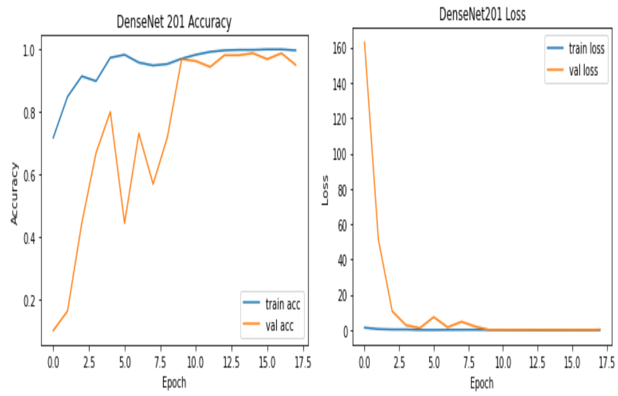

Figure-9. DenseNet 201 accuracy and loss graph.

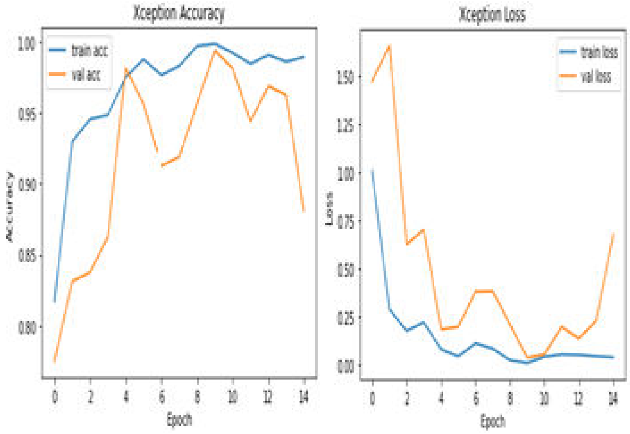

Figure 12. ResNet152V2 accuracy and loss graph.

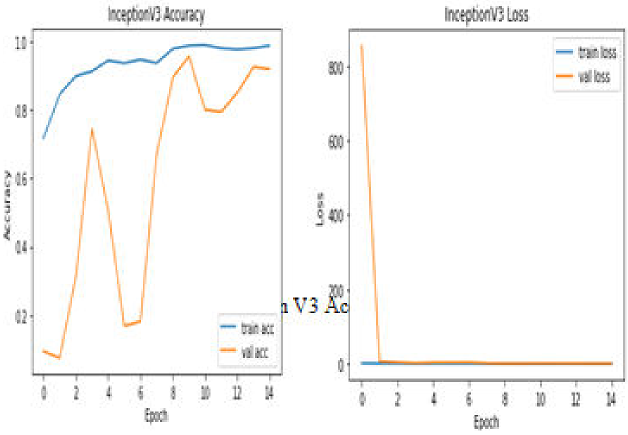

Figure-10. Inception V3 accuracy and loss graph.

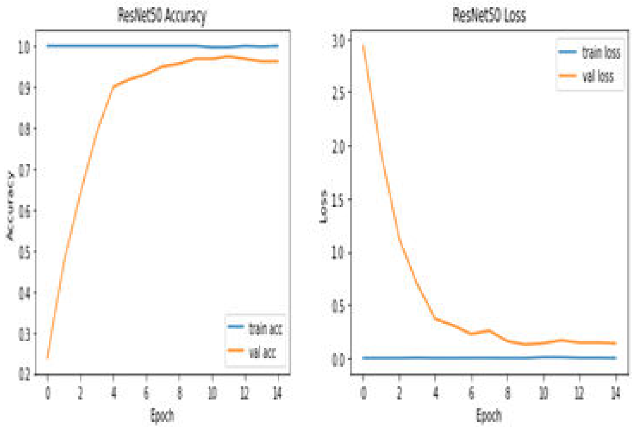

Figure 13. ResNet50 accuracy and loss graph.

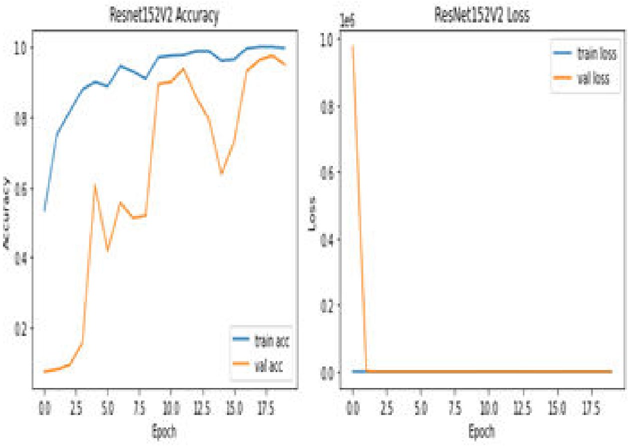

Figure-11. MobileNet accuracy and loss graph.

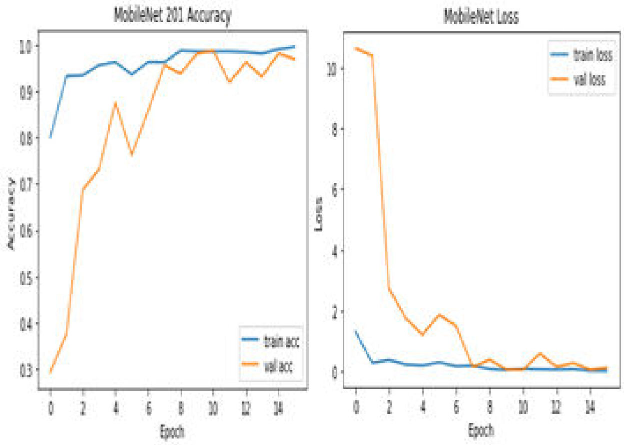

Figure-14. Xception accuracy and loss graph.

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RECOMMENDATION

Future researchers can evaluate the best model that can be derived when categories in a dataset are few using different datasets to increase the accuracy level for the models utilized in this work.

Table-3. Evaluation of each model by its weight size, the loading time and accuracy.

Model	Weight Size	Loading Time (seconds)	Accuracy (Percent)
DenseNet 201	78.7 MB	5	96.87
InceptionV3	91.7 MB	1	92.50
MobileNet	16.8 MB	2	94.99
RenseNet152V2	232 MB	2	95.62
RenseNet50	98.2 MB	1	91.87
Xception	87.6 MB	5	97.5

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