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Automatic identification of native trees using MobileNetV2 model

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ABSTRACT

In protecting our biodiversity, knowledge of tree species is vital. However, not all people are familiar with the trees present in the community which can affect their ability to fully protect the trees. In this premise that the researchers decided to conduct this study to support the sustainable forest management project in the Province of Quirino through the creation of a model of automatic identification of native trees, using the leaves of the trees, found within the Quirino Forest landscape. The model aims to help residents with accessible tools for tree identification which can be used in the conservation efforts within the province. Transfer learning for deep learning, one of the latest advancements in image processing, shows potential for tree identification because the method dodges the labor-intensive feature engineering. Using the Quirino Province native trees leaf/leaflet images dataset, which was annotated by foresters, the MobileNetV2 convolutional neural network was evaluated systemically in this paper. The result shows that the best model version to classify the native trees based on their leaves or leaflets is the one produced using 800 training steps which yields an overall accuracy of 89.61%. The result attained for the tree identification indicates that the proposed technique might be an appropriate tool to assist humans in the identification of native trees found within the landscape of Quirino and can provide reliable technical support for sustainable forest management.

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1. INTRODUCTION

The environment is fast abating worldwide and the degradation rate is mainly the consequence of direct and indirect human actions [1]-[3]. Developing precise knowledge of the identity and the geographic distribution of different plants, of which trees are a part, is indispensable for future environment conservation [4]. Hence, fast and correct plant and tree identification is a key part of the successful study and management of the ecosystem [5], [6].

Plant identification, including tree identification, is not the sole responsibility of experts in the field. It is also valuable that all the components of society should be involved. It is also the responsibility of all people from all walks of life from landscape architects, botanists, horticulturists, conservationists, ecologists, foresters, and biologists to the general public like tourists, mountain climbers, hikers, and nature lovers [5].

However, the identification of plants and trees using the conventional method is not only labor-intensive, complicated, and exasperating for non-experts but it also requires proficiency in plant and tree identification that can only be obtained through intensive education, experience, and training [2]. In addition, the circumstances are further aggravated by the rising scarcity of experienced experts who can identify plants [7], [8] including trees. These are the reasons why recently, various researchers in other places started different methods of plant identification such as automation.

The spread of many technologies like digital imaging devices, faster and stronger mobile and computer equipment, cloud databases, and advanced strategies in computing such as image processing makes the automation of the process of plant identification possible. Image processing performs operations on an image to extract some useful information from it. This method has been used around the world in different domains such as agriculture [9]-[11], education [12], tourism [13], and forestry [14] to name a few.

In the Philippines, image processing technique has been applied in forest and/or tree protection recently. Some of these endeavors include the identification of mango varieties [15], [16], artocarpus trees [17], coffee trees [18], lanzones [19], [20], coconuts [21], and urban greening tree species [22]. Also, image processing was utilized in forest mapping and classification of forest types with tree species identification using light detection and ranging (LiDAR) data [23].

Meanwhile, in the province of Quirino, a province located at the slopes of the Sierra Madre Range, is home to a diverse array of native tree species, such as Molave, Himbabao, Anabiong, and Antipolo to name a few, that must be preserved and protected due to their significance in environmental health, ecological services, and local economic activities. These native trees form a substantial forest cover that supplies drinking water, supports agricultural irrigation, provides habitat for endangered species native to the province, and shields the area from floods and other extreme weather events exacerbated by climate change. However, the forest cover was reportedly diminishing due to the increase in agricultural production in forest land areas [19].

Efforts have been made in the previous years through the implementation of projects geared towards sustainable forest management in the province like tree planting and raising of community familiarity about trees. If people become familiar with different tree species and their needs, people can better protect and care for trees effectively. Familiarity with trees allows the residents within Quirino Province to identify the ecological role each native tree plays, allowing them to appreciate more and actively protect trees in their communities. However, not all residents can learn and be familiar with the native trees present in the community which can affect their ability to fully protect the native trees. In this premise that the researchers decided to conduct this study to support the sustainable forest management project through the creation of a model of automatic identification of native trees found within the Quirino Forest landscape. The model aims to help residents with accessible tools for tree identification which can be used in the conservation efforts within the province.

The primary objective of this study is to build an automated identifier model of native trees found in the landscape of Quirino Province through an image processing technique. Specifically, it sought to (i) build the Quirino Province native trees leaf/leaflets images dataset; (ii) train the identifier to produce the identification model; and (iii) test the identifier to give an estimate for the identification accuracy. The researchers captured simple leaf and compound leaf leaflet images of 13 out of the 51 native trees listed in the "Field Guidebook on Native Trees found within the Quirino Forest landscape [24]".

Inspired by the deep learning breakthrough in tree identification using image processing, this work utilizes a deep learning model, specifically MobileNetV2 convolutional neural network, through transfer learning for image-based automatic identification of native trees. The model created can be used in designing an up-to-date computer vision tool automating the process of trees identification in the province of Quirino which is expected to benefit field researchers, land owners and managers, educators, learners, public servants, and the interested public and will eventually help communities in building sustainable forest management.

2. RELATED LITERATURE

The advancement of computer image processing technology makes it possible for the automatic identification of plant and trees species. In other countries, one of the first to develop modern deep learning advancement in plant species identification has 99.7% accuracy on 44 species from the Royal Botanic Gardens in England [25]. There is also this existing plant database called Leafsnap that covers plants found in the North Eastern United States and is first introduced as a part of a mobile application called LeafSnap [26].

In the Philippines, image processing technique has been applied in forest and/or tree protection recently. Some of these endeavors include the identification of mango varieties [27], [28], artocarpus trees [17], [29], coffee trees [30], and coconuts [31]. As of the moment, no studies have yet been reported dedicated to the automatic identification of the country's native trees. With the above mentioned realities established in the background, this study focuses on the identification of native trees found in the landscape of Quirino Province using image processing, particularly the transfer learning technique.

3. METHOD

There are three main activities performed in this study as shown in Figure 1, namely: image dataset building; training the classifier; and finally, testing the classifier.

Figure 1. The methodology of the study

3.1. Building the images dataset

During the building of the image's dataset, the researchers acquired images from an existing Quirino Forest trees leaf/leaflet images dataset located at the Data Mining Laboratory of Quirino State University-Cabarroguis Campus, Computer Science Department and by capturing leaves and leaflets of different native trees found in the province of Quirino. There were 13 species of native trees considered for this study. Seven (7) species of trees were lifted from the existing dataset of Quirino Forest trees and six (6) species of native trees were gathered personally by the researchers using digital cameras and smartphones having at least 20-megapixel camera system.

There are 13,937 images collected which were saved in a new local database ready for annotation. The images were then annotated by foresters. The images were annotated using the local names of the native trees. The 13,937 annotated images underwent data cleansing. Images with a leaf or leaflet that were taken too far were removed. The 13,832 images passed the cleansing as shown in Table 1. The 13,572 images were used as training data, and the remaining 260 images were used as a test dataset.

Table 1. Datasets distribution of images

Dataset	Number of images	Directory
Training data	13,572	Training dataset
Test data	260	Test dataset
Total	13,832	

3.2. Training the classifier

In this part of the study, Python 3, the Google Colaboratory Notebook, and the TensorFlow 2.4 machine learning library were utilized. The researchers implemented deep learning using the transfer learning technique in building the model. Transfer learning is a technique that uses a pre-trained model and reuses it in a new model, it is popularly known as retraining. Transfer learning is a technique that uses a pre-trained model and reuses it in a new model, it is popularly known as retraining. The pre-trained model obtains the knowledge from the large dataset, which is represented as the weights in the network. Those weights are then used in another network for a different task with a different dataset. Therefore, instead of training the second network from scratch, usually with a small dataset, its "transfers" the learned features of the first network to the second network. The network learns about the specific features for a particular task in the last layers of the network. Therefore, in transfer learning, the weights of the base network or model are frozen. Then, the learning process is done to the last layer of the network, which is generally a fully-connected layer, so that the network can learn the specific features to classify the new dataset [32].

In this study, the researchers reused the capabilities from the MobileNetV2 neural network and trained the native trees identification layer on top. MobileNetV2 is a Google-based developed architecture that is pretained on million images of 1,000 different classes [33]. MobileNetV2 is an advanced neural network architecture that executes better on mobile devices where it does not have to train the model from scratch, it only changes the last output layers according to the domain. Figure 2 shows the basic architecture of MobileNetV2.

To come out with improved results, the researchers tried altering the details of the learning process by changing the number of training steps to experiment on what works best for the model. The number of training steps was changed from 400, 500, 800, and 1,000. Validation accuracy for each training step was recorded. The accuracies recorded were then compared and the corresponding training step with the highest validation accuracy was noted and underwent a test for overfitting.

With the use of the TensorBoard, a series of steps output during retraining was visualized showing validation accuracy and the cross entropy. The accuracy and cross-entropy values of the model were assessed for overfitting or underfitting occurrences. After training was complete, the following two files were generated: (i) retrained_graph.pb, which contains a version of the selected network with a final layer retrained on the identification categories; and (ii) retrained_labels.txt, which is a text file containing labels. The files can be used in developing an automatic Quirino Province native tree identification system.

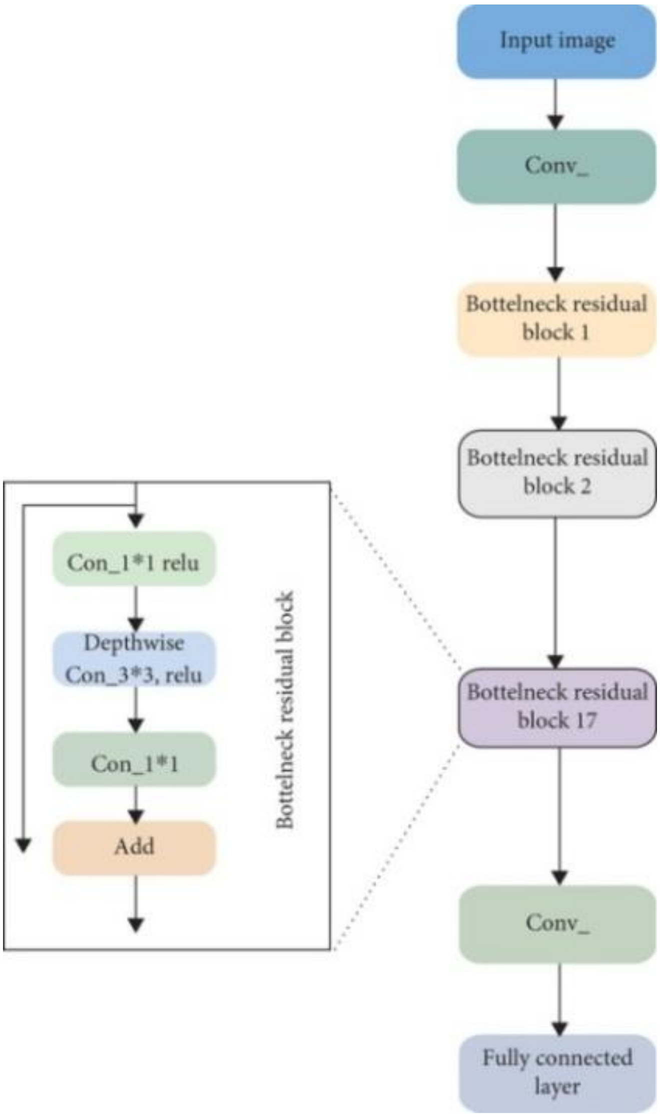

Figure 2. The basic architecture of MobileNetV2 [34]

3.3. Testing the classifier

To test the model, a script of Tensorflow's named label_image.py was used. For each execution, the model prints a list of native tree identification labels with the correct identification label on top. The result of the testing was compared to the annotation done by the foresters to determine the accuracy. Testing all the 260 images on the test_dataset, the test accuracy was derived.

4. RESULTS AND DISCUSSION

4.1. The quirino native trees image dataset

The images gathered were annotated based on their species as presented in Table 2. There were thirteen categories since there are 13 native trees considered. The categories used were Kamagong, Bignai, Duhat, Himbabao, Antipolo, Alim, Anabiong, Banaba, Banato, Ipil, Narra, Bulala, and Molave. Examples of annotated image data for each species are shown in Figures 3 to 15.

Table 2. Categories used in annotation

Figure No.	Category (species)	Total number of annotated images used in training	Total number of annotated images used in testing
Figure 3	Kamagong	1,010	20
Figure 4	Bignai	1,005	20
Figure 5	Duhat	1,010	20
Figure 6	Himbabao	1,015	20
Figure 7	Antipolo	1,020	20
Figure 8	Alim	1,069	20
Figure 9	Anabiong	1,021	20
Figure 10	Banaba	1,090	20
Figure 11	Banato	1,083	20
Figure 12	Ipil	1,073	20
Figure 13	Narra	1,068	20
Figure 14	Bulala	1,100	20
Figure 15	Molave	1,008	20
	Total	13,572	260

Figure 3. Kamagong

Figure 4. Bignai

Figure 5. Duhat

Figure 6. Himbabao

Figure 7. Antipolo

Figure 8. Alim

Figure 9. Anabiong

Figure 10. Banaba

Figure 11. Banato

Figure 12. Ipil

Figure 13. Narra

Figure 14. Kapulasan

Figure 15. Molave

4.2. The result of the training

The labeled dataset underwent retraining procedures using the MobileNetV2 network model. The final validation accuracies for each of the retraining processes conducted were recorded. The validation accuracy is the precision of a group of images that were randomly selected by the model from the training data. The validation accuracy is the true measure of the performance of a network model and was used in this study for the selection of which is the right one to implement in building the native tree identifier.

Table 3 presents the result of the retraining process. Based on the table, the model was retrained using 400, 500, 800, and 1,000 training steps. The number of training steps means training using a batch size of training data at a time. The training steps were adjusted from 400 to 1,000 to run through the performance of the MobileNetV2. Comparing the derived final validation accuracies, MobileNetV2 with training step 800 showed the highest accuracy as compared to the other training steps with an accuracy of 88.83%.

Also, the training accuracy and cross-entropy of the network were observed using the TensorBoard. Figure 16 depicts the variation in accuracy while Figure 17 presents the variation of cross-entropy on the native tree's dataset using MobileNetV2 with 800 training steps. Two lines are shown for each graph. The red lines show the results of the model on the training data. While the blue lines show the results of the validation set.

The training accuracy presents the portion of the images utilized in the current training batch that were labeled with the correct class. The difference between the training accuracy and the validation accuracy is based on images that the network has been able to learn from, so the network can overfit the noise in the training data. If the training accuracy continues to rise while the validation accuracy decreases, that means the network is overfitting and memorizing particular features in the training images that aren't helpful more generally. This is a much better measure of the true performance of the network. As the training process continues, the reported accuracies should improve and should not form a straight line.

At the end of the training, the final training accuracy recorded was 89.9% which is slightly higher than the validation accuracy. Nevertheless, as shown in the graph in Figure 16, MobileNetV2 shows no sign of overfitting because the accuracy of the training did not form a straight line and the validation accuracy continued to progress alongside the training accuracy. This means that the model did not memorize the training set but instead it understands general patterns in the data.

Table 3. Result of the retraining processes

Model	Training steps	Final validation accuracy
MobileNetV2	400	82.63%
MobileNetV2	500	86.75%
MobileNetV2	800	88.83%
MobileNetV2	1,000	87.64%

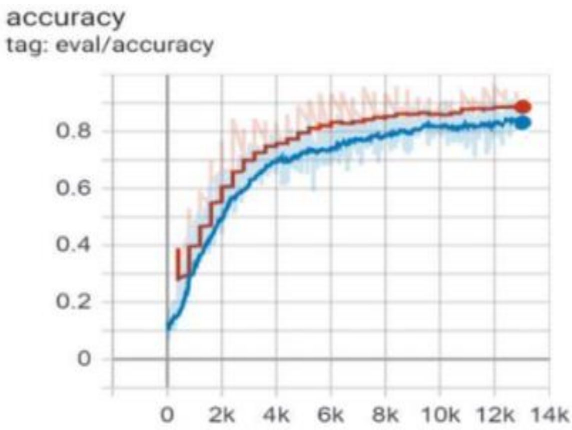

Figure 16. Variation of accuracy on the dataset using MobileNetV2 model

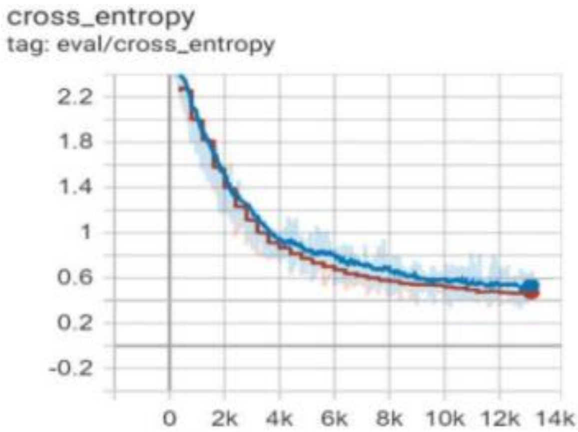

Figure 17. Variation of cross-entropy on the dataset using MobileNetV2 model

On the other hand, cross-entropy is a loss function that shows how well the learning process is progressing. Lower values for loss are better. To substantiate that the MobileNetV2 using 800 training steps was the right model to be adopted for the transfer learning, the training's objective was to make the loss as small as possible, monitoring on whether the loss keeps moving downwards, ignoring the short-term noise.

At the end of the training, the recorded training cross-entropy was 0.455 while the validation cross-entropy was 0.575. The losses incurred were fairly low as shown in Figure 17. This is an indication that the learning process progressed. The variations of the accuracy and cross-entropy on the dataset illustrated that the MobileNetV2 neural network with 800 training steps was suitable for this project.

4.3. The result of the testing

With the result of the image processing, an identifier was created and tested in a new dataset named test_dataset. There are 260 images on the said dataset labeled test_1.jpg, test_2.jpg, and so on. Of the 260 images, 233 images were correctly identified by the identifier. This means that there was 89.61% test accuracy. Table 4 illustrates a comparison between the outputs of the identifier and the annotation.

Table 4. Comparison of sample outputs of the identification

Figure No.	Image name	Identifier	Annotator
Figure 18	test_1.jpg	Antipolo	Antipolo
Figure 19	test_25.jpg	Ipil	Ipil
Figure 20	test_59.jpg	Kapulasan	Banaba
Figure 21	test_100.jpg	Himbabao	Himbabao
Figure 22	test_201.jpg	Anabiong	Anabiong

Based on the table, image test_1.jpg shown in Figure 18 was classified by both the identifier and the annotator as Antipolo. However, the identifier had a different result for image test_59.jpg in Figure 20 from that of the annotator. The annotator indicated the image is a Banaba but the identifier indicated it as Kapulasan.

Nevertheless, it can also be observed that images test_25.jpg in Figure 19, test_100.jpg in Figure 21, and test_201.jpg in Figure 22 had the same outputs from both the identifier and the annotator which means that the identifier has correctly identified the given images. The result of the testing shows that the performance of the proposed method is comparable to human experts.

Figure 18. test_1.jpg

Figure 19. test_25.jpg

Figure 20. test_59.jp

Figure 21. test_100.jpg

Figure 22. test_201.jpg

5. CONCLUSION

In this study, image processing was applied. The native trees' image data were identified based on what species they are and labeled them using their local names. MobileNetV2 neural network model was applied to the native tree's leaf/leaflets training dataset via transfer learning technique. Transfer learning was implemented because it often speeds up the process of training the model on a new task, and can also produce an accurate and effective model overall. Moreover, transfer learning is a technique in computer vision that allows developers to circumvent the need for lots of new data. This is the reason why it is suggested for projects with few data sources just like this study.

Training results show that MobileNetV2 with 800 training steps produces higher accuracy. The MobileNetV2 method was able to train and test 13 native trees and achieves a validation accuracy of 88.83% which is comparable to human experts. To verify the general adaptability of the model, it was tested to a native trees test dataset and achieved an accuracy of 233 out of 260 or 89.61%. Thus, the proposed method showed potential for identification because this is very close to those obtained by image processing researchers conducted in recent years, however, the result can still be increased by adding additional images in the dataset.

For future works, the researchers should complete the native trees within the Quirino Province landscape as described in the above mentioned book; improve the accuracy of the native trees' image identifier by gathering and adding more images for each tree; use the traditional image processing and other network models and compare the accuracies with the result of this study, consider processing compound leaves images as an enhancement to the leaflet images, and finally use the final model in developing a system for automatic native trees identification in the Province of Quirino that can assist in monitoring native trees and reliable technical support for sustainable forest management.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Melidiossa V. Pagudpud	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Reynold A. Rustia	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Wilyn S. Marzo,	✓			✓	✓	✓	✓		✓		✓	✓	✓	✓
Joel G. Carig	✓	✓		✓	✓	✓	✓	✓	✓				✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, MVPagudpud, upon reasonable request.

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