

## Development of durian leaf disease detection on Android device

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### ABSTRACT

Durian is exceedingly abundant in the Philippines, providing incomes for smallholder farmers. But amidst these things, durian is still vulnerable to different plant diseases that can cause significant economic loss in the agricultural industry. The conventional way of dealing plant disease detection is through naked-eye observation done by experts. To control such diseases using the old method is extensively laborious, time-consuming and costly especially in dealing with large fields. Hence, the proponent's objective of this study is to create a standalone mobile app for durian leaf disease detection using the transfer learning approach. In this approach, the chosen network MobileNets, is pre-trained with a large scale of general datasets namely ImageNet to effective function as a generic template for visual processing. The pre-trained network transfers all the learned parameters and set as a feature extractor for the target task to be executed. Four health conditions are addressed in this study, 10 per classification with a total of 40 samples tested to evaluate the accuracy of the system. The result showed 90% in overall accuracy for detecting algal spot, cercospora, leaf discoloration and healthy leaf.

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## 1. INTRODUCTION

Durian is exceedingly abundant in the Philippines, specifically in Davao City. Which the city is the top producer of Durian for about 60% of the country's total harvest. It's one of the most valued fruit crops providing sustainable incomes for smallholder farmers creating up to 80% of the industries. But amidst these things, there are still difficulties undergone in cultivating Durian. One of the key problems for durian cultivation is plant diseases namely phytophthora and pythium, causing the disease in the roots and the stem rots [1]. The stern effect of these diseases led to conduct a partaking research approach to advance and promote management strategies [2]. Phytophthora Palmivora is not only evident in durian but also in other plant species [3]. Phomopsis Durionis, another pathogen that caused the leaf spot diseases in durian growing areas in eastern Thailand [4]. With this, plant diseases are responsible for the significant economic losses experienced in the worldwide agricultural industry [5]. This is one of the foremost reasons why advanced disease detection and prevention in crops are imperative [6]. Plant monitoring performed by an expert agriculturist through naked eye observation is important and necessary to control the spread of plant diseases [7], [8]. But this method is proven to be time-consuming, laborious and costly especially in dealing with large fields [9]. Researches are already utilizing machine learning techniques for fast and more accurate plant disease detection [10]. In agriculture and other institutions in India, the use of transfer learning and image

processing for disease identification is being directed [11]-[17]. A study in leaf rot disease detection using image processing was implemented. The scheme in capturing the leaf image for input data is through flatbed scanner which is far more favorable than the conventional way. But this method is chiefly not convenient because the digital image of the leaf sample captured for input has size restrictions. The image has to be into a smaller dimension of size 16x20 sq.cm. This is enforced to save about 30% of disk storage space and increase CPU processing time. Adding on, the output after the whole process is mainly displayed in a computer monitor [18].

The proponents are on the grounds of making the disease detection process fast, convenient and accessible through the use of mobile phone. This study aimed to develop a standalone mobile application for 'Durian leaf disease recognition' using the transfer learning approach where a pre-existing neural network is taken and adjusted slightly to analyze data and identify diseases in durian leaves. By adopting transfer learning, all calculations and processes are done in the device making leaf disease detection fast, convenient, accessible and efficient. It does not need any internet connection or cloud-based transactions to generate the predicted output making a standalone mobile application possible.

## 2. RESEARCH METHOD

### 2.1. Conceptual framework

Shown in Figure 1 the procedures to follow in developing the mobile application. The images of durian leaf acquired from the field will serve as the input. After the image acquisition, the pre-trained model which is MobileNets with Tensorflow will process and analyzed it. The results in the processing and analysis will be used for the classification to occur. After the data is classified, the identified disease will be displayed in the Android mobile application.

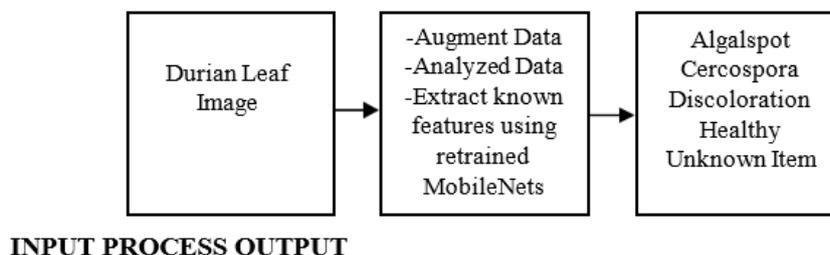


Figure 1. Conceptual framework

### 2.2. Durian leaf samples

Figure 2 displays the training and testing images acquired from the Department of Agriculture XI and Durian Farms in the Davao Region. Four health condition was considered: 2 leaf diseases such as Algalspot and Cercospora, 1 leaf discoloration and 1 healthy leaf. There are 500 images in total that have been randomly taken. The images were classified and verified by experts and were augmented that caused to escalate the number of samples to 1070 images and were resized according to the input size of the neural network for dataset preparation.

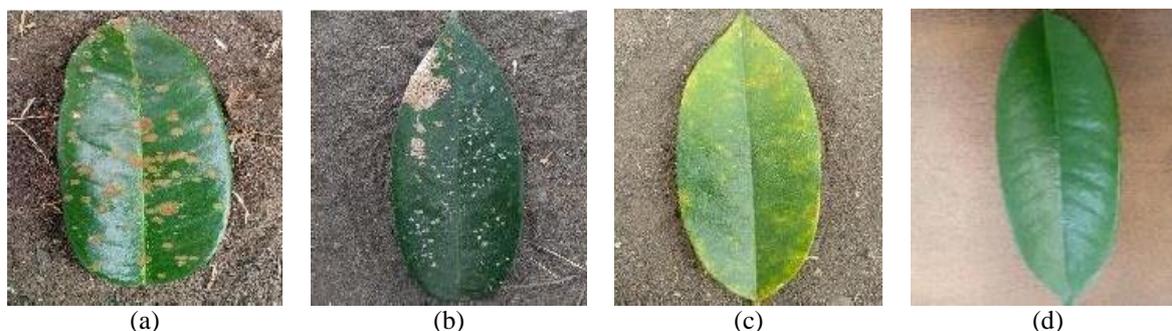


Figure 2. Durian leaf image sample; (a) Algalspot, (b) Cercospora, (c) Discoloration, (d) Healthy

**2.3. CNN network architecture**

Figure 3 presents the general architecture of convolutional neural network. Which is a deep learning approach that is widely used for solving complex problems [19]. In the Figure 3, it uses leaf images as input followed by the convolutional layer operations and the fully connected layers.

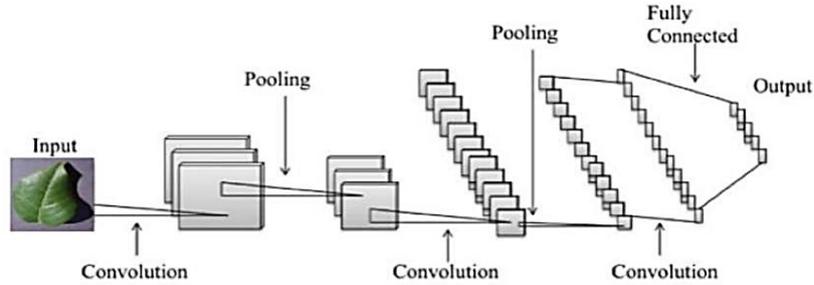


Figure 3. CNN network architecture [20]

**2.4. MobileNets model**

Figure 4 Illustrates the Mobilenets model that is utilized in this study. This convolutional neural network model is built primarily from depth wise separable convolutions [21]. Optimized to be executed using minimal possible computing power and enhanced latency on a smartphone device. Mobilenets has two surface parameters which are the width multiplier to thin the network and the resolution multiplier that changes the input dimensions of the image [22], [23]. Both are tuned to resolve the resource and accuracy trade-off problem of the target task.

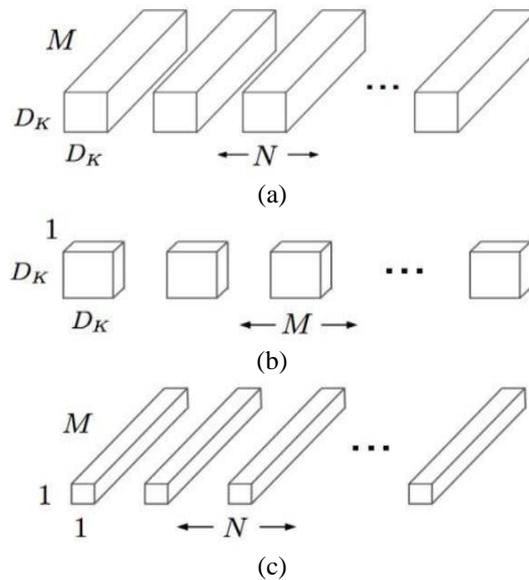


Figure 4. Mobilenets model [22]; (a) Standart convolution filters, (b) Depthwise convolution filter, (c)  $1 \times 1$  convolution filters called pointwise convolution in the context of depthwise separable convolution

**2.5. Research method**

Shown in Figure 5 the research method applied in this study. It comprises two primary stages: the retraining and the testing stage. The first stage begins with the preparation of the collected data images then implementing the method of transfer learning using the CNN MobileNets model. The output files protobuf and label.txt is embedded into the created Android app. The second stage is the process of testing the output file from the retraining process both in PC and Mobile.

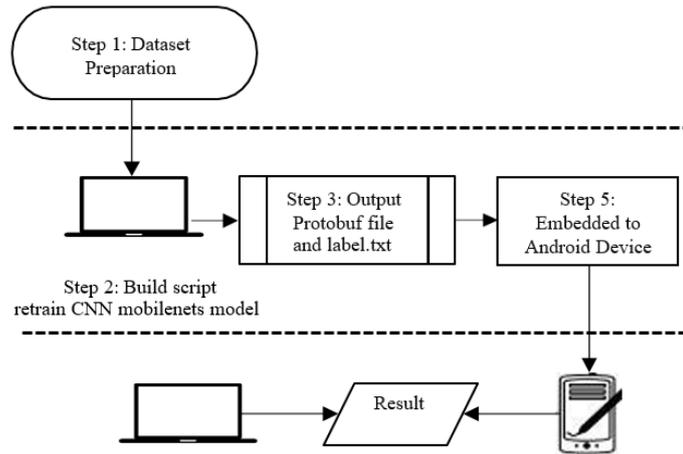


Figure 5. Research method

**2.6. Main data flow graph using TensorBoard**

Figure 6 shows the data flow graph, starting from bottom to top for the created durian leaf disease detection system applying the transfer learning approach with the model MobileNets. The image was extracted using TensorBoard: Tensorflow’s visualization toolkit for machine learning experimentation. Transfer learning addresses to improve a model from one domain by transferring all of the information processed from one to the other related domain [24]. It is considered to be more efficient for it uses a small quantity of data to train the model and attain high precision results with short training time since prior know. Compared to the traditional neural network that needs highly extensive computational power and long period time for training.

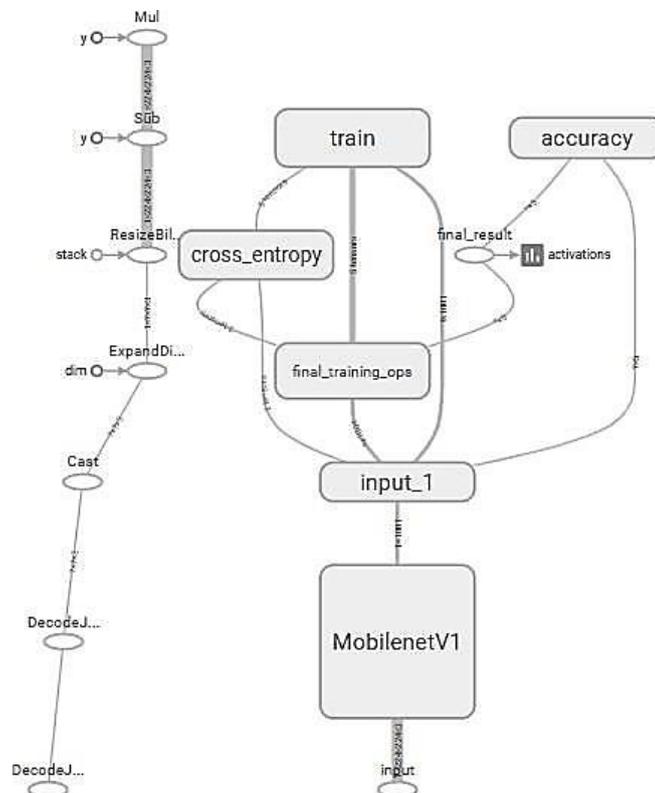


Figure 6. Main data flow graph using TensorBoard

## 2.7. Software design

Figure 7 displays the process flow software design for the image classification implementing the transfer learning approach. In this process, a network that is the MobileNets is pre-trained with a large-scale of general datasets namely ImageNet to effectively function as a generic template for visual processing. The pre-trained network transfers all the learned parameters and is set as a feature extractor for the target task to be executed. The final classification layer of the CNN MobileNets model is removed, freezing the other layers and retraining the last layer with the new set of target images and applying fine-tuning for the parameters.

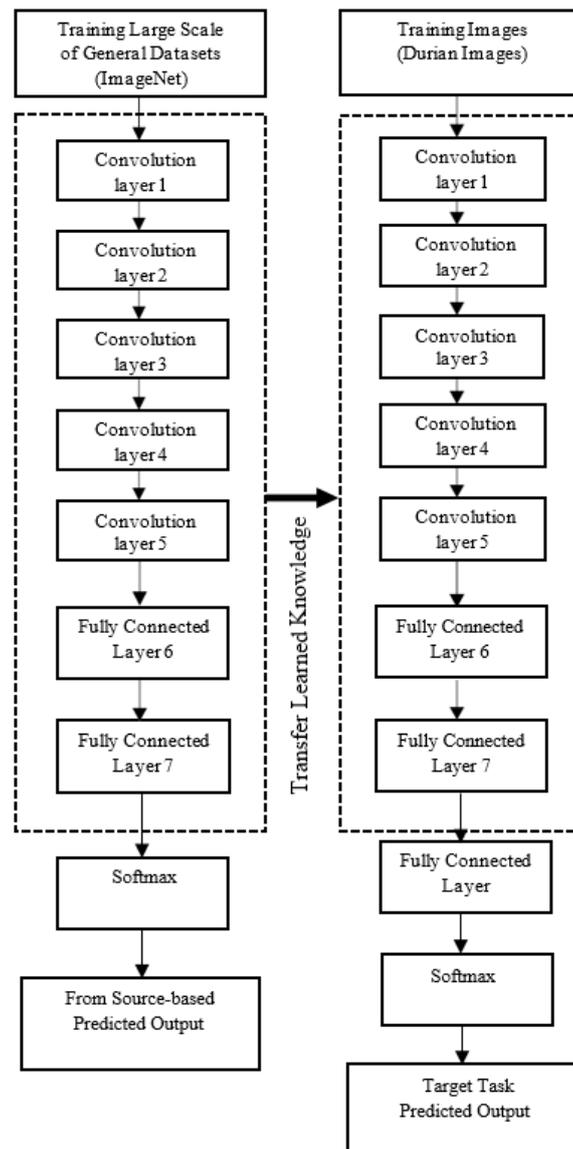


Figure 7. Process flow for image classification

## 3. RESULTS AND DISCUSSION

### 3.1. Data set

The proponents gathered data samples from the Department of Agriculture and Durian farms in Davao Region to be classified for the datasets. 70 samples were given to the regional crop protection center for verification where 18 samples of Healthy leaves and 13 samples of Leaf Discoloration were confirmed through bare observation by the agriculturist. The remaining 39 samples were presented to the RCPC Laboratory for isolation, incubation and laboratory testings. The RCPC researchers used microscopic

procedures and other lab tools for leaf disease analyzation and identification process. After the procedures, 22 were verified for Algalspot and 17 for Cercospora. Figure 8 displays the graph of samples being distributed as Algalspot disease, Cercospora diseases, leaf discoloration and healthy leaf using the conventional procedures.

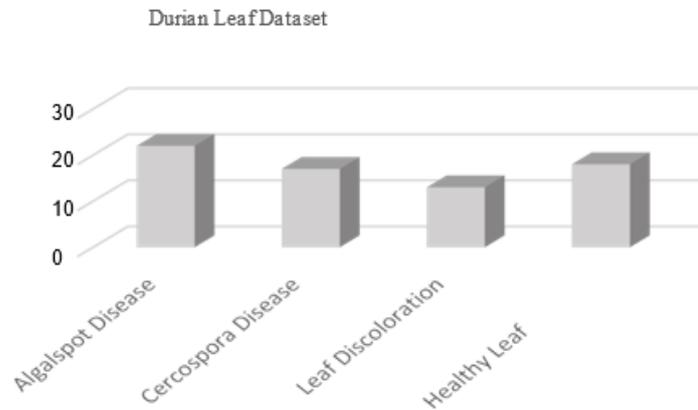


Figure 8. Durian leaf datasets

### 3.2. Magnified algalspot and cercospora disease

Figures 9 and 10 shows the microscopic results of Algalspot and Cercospora disease after 4 days of incubation done by a plant pathologist in the regional crop protection Center Laboratory using the sporulation technique.

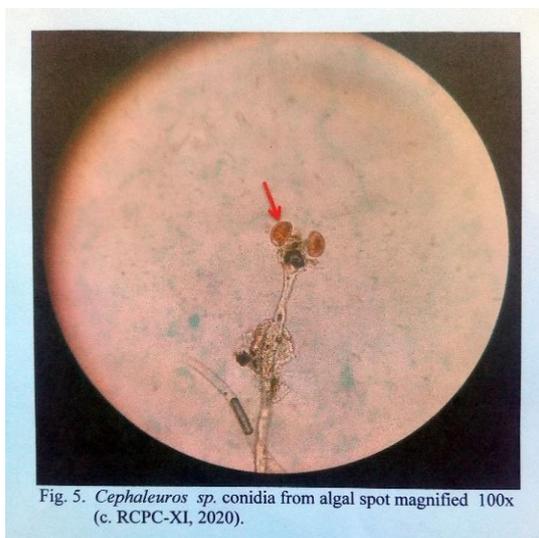


Figure 9. Magnified algalspot disease

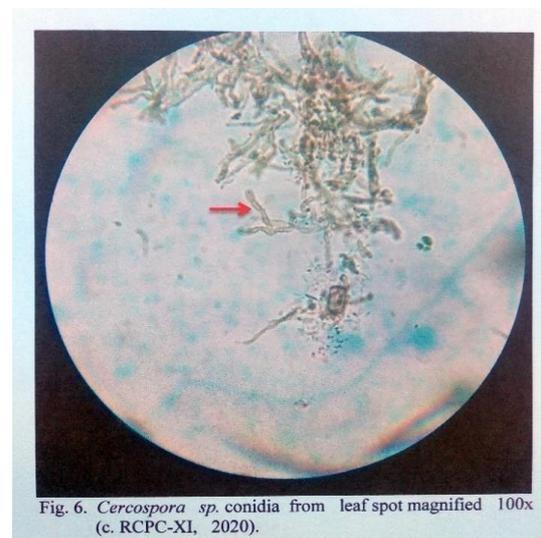


Figure 10. Magnified cercospora disease

### 3.3. Data analysis

The result shown in Table 1, is the durian leaf disease prediction analysis conducted to 40 testing samples using a confusion matrix [25]. The leaf disease was already classified and labeled before subjected to testing. The computation revealed that Algalspot Leaf Disease yielded to 80% or 8 out of 10 samples. Cercospora leaf disease yielded to 90% or 9 out of 10 samples. Leaf discoloration yielded to 90% or 9 out of 10 samples. Lastly, healthy durian leaf yielded to over 100% or 10 out of 10 samples. As a result, from the 40 samples that are tested, 36 were correctly classified and resulted in 90% overall accuracy

Table 1. Predicted data

	Als	Crp	Lfd	Ht y	Classification Overall	PA
Actual Data	Als	8	0	0	10	80%
	Crp	0	9	0	1	90%
	Lfd	0	0	9	1	90%
	Hty	0	0	0	10	100%
	TOTAL	8	11	9	12	40
	UA (%)	100	81	100	83	
	OA				90%	

Legend: Als = Algalspot; Crp = Cercospora; PA = Producer Accuracy; OA = OverallAccuracy; Hty = Healthy Leaf; UA = User Accuracy; Lfd = Leaf Discoloration

**3.4. Accuracy results**

Represented in Figure 11. The accuracy results from the processed retrained model with the help of TensorBoard. The result produced 96% for the training dataset and 88% for the validation dataset.

**3.5. Cross entropy results**

Figure 12 displays the cross-entropy loss results from the processed retrained model with the help of TensorBoard. The result produced 12% for the training dataset and 53% for the validation dataset.

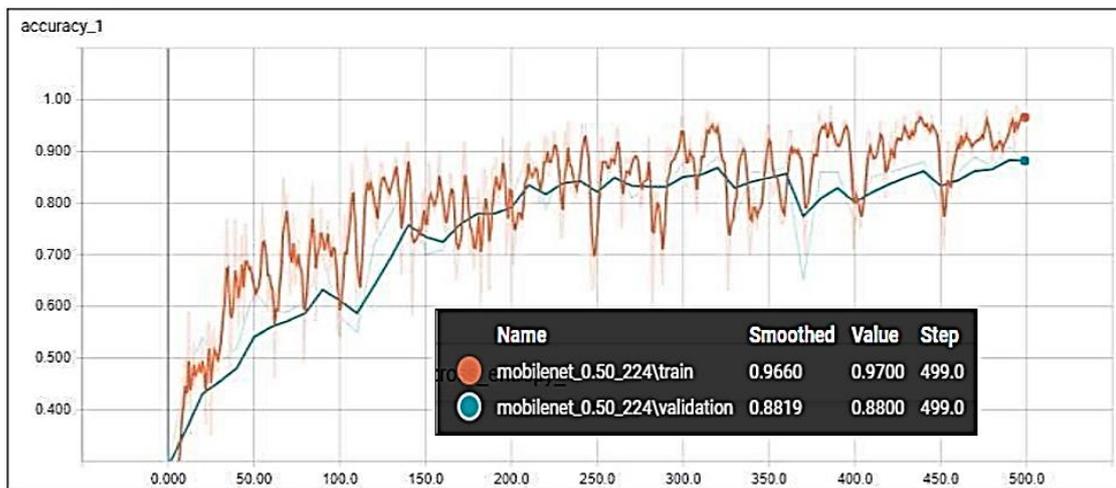


Figure 11. Accuracy result figure

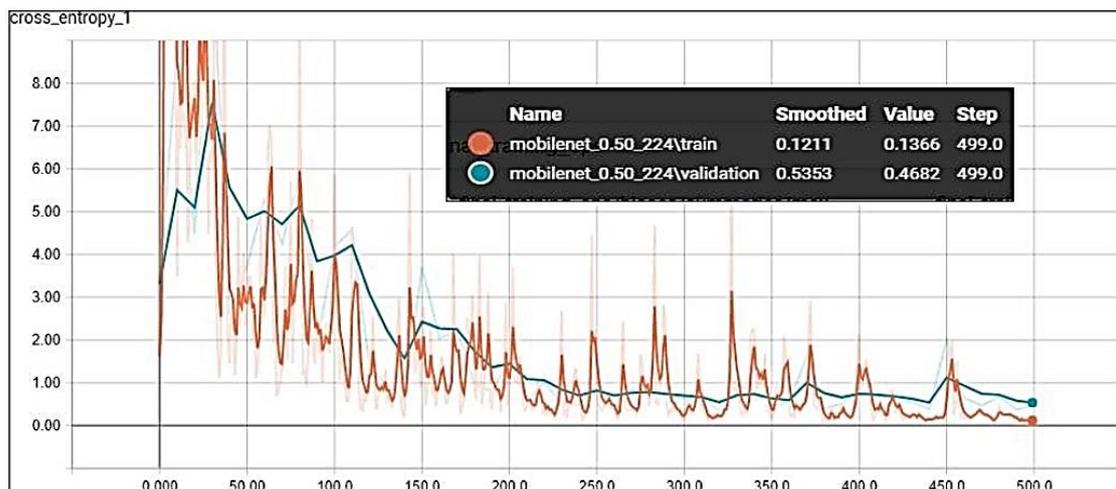


Figure 12. Cross entropy result

### 3.6. Graphical user interface

Presented in Figure 13 the user graphical interfaces of the developed mobile app. There are four main button options to choose from which are: About, capture image, select image and control management. About button presents the guidelines on how to use the mobile app and the information about the app and its developers. In the capture image button, the user can capture a target durian leaf image for classification. In select image button, the user can select a durian leaf image from the gallery for classification. Lastly, the control management button presents essential information about leaf diseases and as well as the control measures to be applied to stop the manifestation of the disease in the durian leaves.

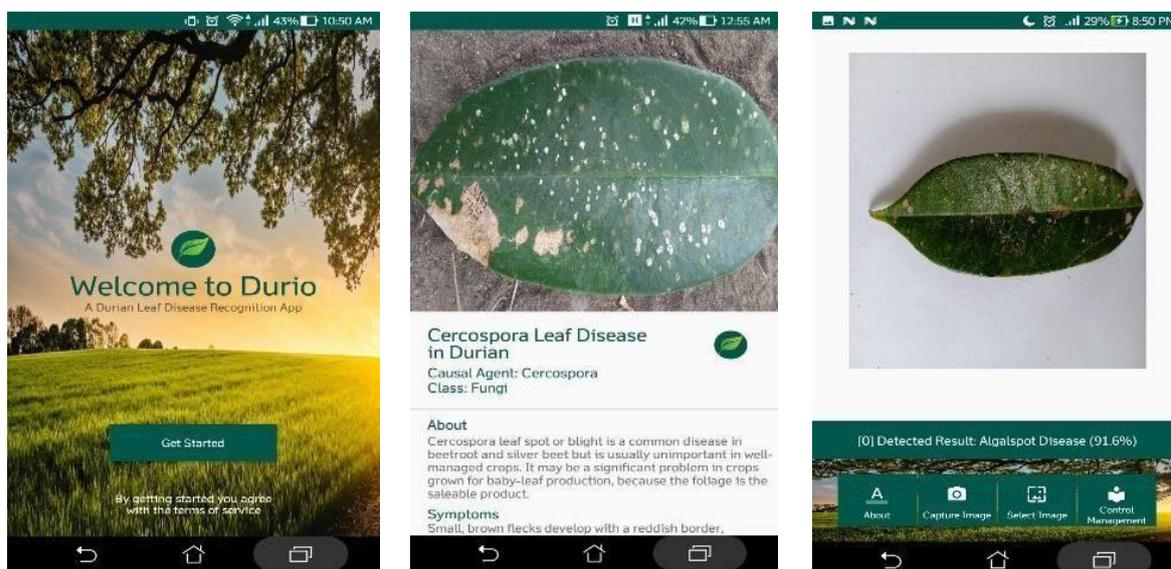


Figure 13. Graphical user interface

## 4. CONCLUSION

The study was able to implement a standalone mobile application that can classify durian leaf diseases with the applied transfer learning approach and retrained CNN MobileNets model. The classifier was able to correctly detect 36 out of 40 samples which accumulated an overall accuracy of 90%. For the future work and improvement of the study, it is recommended to add another classifier in addition to the retrained CNN model such as logistic regression to improve accuracy and the efficiency of the whole system.

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## REFERENCES

- [1] X. Li, Z. Deng, Z. Chen and Q. Fei, "Analysis and Simplification of Three-Dimensional Space Vector PWM for Three-Phase Four-Leg Inverters," in *IEEE Transactions on Industrial Electronics*, vol. 58, no. 2, pp. 450-464, Feb. 2011, doi: 10.1109/TIE.2010.2046610.
- [2] R. Daniel *et al.*, "Development of disease management recommendations for the durian and jackfruit industries in the Philippines using farmer participatory research," *Food Security*, vol. 6, no. 3, pp. 411-422, 2014, doi: 10.1007/s12571-014-0352-6.
- [3] D. I. Guest, G. Martinez, G. A. Sarria, F. Varon, G. A. Torres and A. Drenth, "Bud Rot Caused by *Phytophthora palmivora*: A Destructive Emerging Disease of Oil Palm," *Phytopathology*, vol. 106, no. 4, pp. 320-329, 2015, doi: 10.1094/PHYTO-09-15-0243-RVW.

- [4] V. Tongstri, P. Songkumarn and S. Sangchote, "Leaf spot characteristics of *Phomopsis durionis* on durian (*durio Zibethinus Murray*) and latent infection of the pathogen," *Acta Univ. Agric. Silv. Mendelianae Brun.*, vol. 64, no. 1, pp. 185-193, 2016, doi: 0.11118/actaun201664010185.
- [5] F. Martinelli *et al.*, "Advanced methods of plant disease detection. A review," *Agronomy for Sustainable Development*, vol. 35, no. 1, pp. 1-25, 2015, doi: 10.1007/s13593-014-0246-1.
- [6] Y. Fang and R. P. Ramasamy, "Current and prospective methods for plant disease detection," *Biosensors*, vol. 5, no. 3, pp. 537-561, 2015, doi: 10.3390/bios5030537.
- [7] N. Petrellis, "Plant disease diagnosis based on image processing, appropriate for mobile phone implementation," *HAICTA 2015*, vol. 1498, pp. 238-246, 2015.
- [8] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Information Processing in Agriculture*, vol. 4, no. 1, pp. 41-49, 2017, doi: 10.1016/j.inpa.2016.10.005.
- [9] S. R. Kamlapurkar, "Detection of Plant Leaf Disease Using Image Processing Approach," *International Journal of Scientific and Research Publications*, vol. 6, no. 2, pp. 73-76, 2016.
- [10] A. Ramcharan, K. Baranowski, P. McCloskey, B. Ahmed, J. Legg, and D. P. Hughes, "Using Transfer Learning for Image-Based Cassava Disease Detection," *Frontiers in plant science*, vol. 8, 2017, doi: 10.3389/fpls.2017.01852
- [11] V. K. Shrivastava, M. K. Pradhan, S. Minz, and M. P. Thakur, "Rice Plant Disease Classification using Transfer Learning of Deep Convolution Neural Network," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XLII-3/W6, pp. 631-635, 2019, doi: 10.5194/isprs-archives-XLII-3-W6-631-2019.
- [12] S. Abisha and T. Jayasree, "Application of Image Processing Techniques and Artificial Neural Network for Detection of Diseases on Brinjal Leaf," *IETE Journal of Research*, pp. 1-13, 2019, doi: 10.1080/03772063.2019.1696716.
- [13] K. R. Aravind and P. Raja, "Automated disease classification in (Selected) agricultural crops using transfer learning," *Automatika*, vol. 61, no. 2, pp. 260-272, 2020, doi: 10.1080/00051144.2020.1728911.
- [14] B. Prakash, A. Yerpude and M. T. Scholar, "Identification of Mango Leaf Disease and Control Prediction using Image Processing and Neural Network," *International Journal for Scientific Research and Development*, vol. 3, no. 5, pp. 794-799, 2015.
- [15] R. P. Narmadha and G. Arulvaidivu, "Detection and measurement of paddy leaf disease symptoms using image processing," *2017 International Conference on Computer Communication and Informatics (ICCCI)*, 2017, pp. 1-4, doi: 10.1109/ICCCI.2017.8117730.
- [16] P. M. Mainkar, S. Ghorpade and M. Adawadkar, "Plant Leaf Disease Detection and Classification Using Image Processing Techniques," *International Journal of Innovative and Emerging Research in Engineering*, vol. 2, no. 4, pp. 139-144, 2015.
- [17] S. D. Khirade and A. B. Patil, "Plant Disease Detection Using Image Processing," *2015 International Conference on Computing Communication Control and Automation*, 2015, pp. 768-771, doi: 10.1109/ICCUBEA.2015.153
- [18] A. K. Dey, M. Sharma and M. R. Meshram, "Image Processing Based Leaf Rot Disease, Detection of Betel Vine (*Piper BetleL.*)," *Procedia Computer Science*, vol. 85, pp. 748-754, 2016, doi: 10.1016/j.procs.2016.05.262.
- [19] S. Indolia, A. K. Goswami, S. P. Mishra and P. Asopa, "Conceptual Understanding of Convolutional Neural Network- A Deep Learning Approach," *Procedia Computer Science*, vol. 132, pp. 679-688, 2018, doi: 10.1016/j.procs.2018.05.069.
- [20] B. Syamsuri and I G. P. K. Negara, "Plant Disease Classification using Lite Pretrained Deep Convolutional Neural Network on Android Mobile Device," *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, no. 2, pp. 2796-2804, 2019.
- [21] L. Kaiser, A. N. Gomez, and F. Chollet, "Depthwise Separable Convolutions for Neural Machine Translation," *arXiv:1706.03059*, vol. 1, 2017.
- [22] A. G. Howar *et al.*, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," *arXiv:1704.04861*, 2017.
- [23] N. R. Gavai, Y. A. Jakhade, S. A. Tribhuvan and R. Bhattad, "MobileNets for flower classification using TensorFlow," *2017 International Conference on Big Data, IoT and Data Science (BIG DATA)*, 2017, pp. 154-158, doi: 10.1109/BID.2017.8336590.
- [24] S. J. Pan and Q. Yang, "A Survey on Transfer Learning," in *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345-1359, Oct. 2010, doi: 10.1109/TKDE.2009.191.
- [25] A. K. Santra and J. Christy, "Genetic Algorithm and Confusion Matrix for Document Clustering," *International Journal of Computer Science Issues*, vol. 9, no. 1, 2012.

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