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E'MELON: Android-Based Watermelon Leaf Disease Detection and Remedy Using TensorFlow and CNN

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RESEARCH ARTICLE INFORMATION	ABSTRACT
Received: July 31, 2024 **Reviewed:** November 08, 2024 **Accepted:** December 07, 2024 **Published:** December 31, 2024	The early detection of watermelon leaf diseases is crucial for effective crop management, yet traditional methods are labor-intensive and require technical expertise. This study aimed to develop an Android-based application using TensorFlow and Convolutional Neural Networks (CNN) to detect and remedy watermelon leaf diseases. The CNN-based software leverages image classification techniques to enhance accuracy and reduce the complexity of previous algorithms. The application was evaluated by 19 randomly selected participants using the ISO/IEC 9126 Software Quality Model, resulting in a weighted mean accuracy score of 4.42, which corresponds to good, which highlights that most respondents agree that the Android application effectively identifies watermelon diseases and provides appropriate treatment recommendations. This rating was determined based on specific criteria such as functionality and reliability. However, the classifier's performance needs improvement, particularly in distinguishing between similar disease symptoms. Feedback from watermelon experts and farmers indicated that while the application is promising, enhancements needed on the delivery of specific data for certain disease categories are needed for ease of understanding. The findings highlight the potential of mobile-based applications in agricultural disease management and the need for further refinement to achieve higher precision.

Keywords: *disease detection, android-based, CNN, TensorFlow, ISO/IEC 9126*

Introduction

Artificial Neural Networks (ANNs) have revolutionized machine learning, with biologically inspired models outperforming previous AI techniques in various tasks. Convolutional Neural Networks (CNNs), a popular ANN architecture, have significantly advanced image processing and speech recognition over the past decade (Albawi et al., 2017). CNNs have been particularly effective in improving leaf disease detection, as highlighted by Reddy et al. (2020). However, Kumar et al. (2020) noted the challenges of implementing image classification on a small scale with limited hardware. While Support Vector Machines (SVMs) can achieve high accuracy with minimal datasets, their performance decreases as the dataset size increases. This limitation makes SVMs less reliable for large-scale applications. Traditional methods of disease detection in watermelon are labor-intensive and require technical expertise, which limits their effectiveness. Diseases can affect all parts of the plant, from roots to fruit, at any stage of crop production, leading to significant losses in quality and yield. Therefore, developing CNN-based solutions for watermelon disease detection can provide more accurate and efficient alternatives to traditional methods, addressing the specific challenges faced by growers.

While the Philippines has good land and an ideal temperature, as well as a diverse crop, the tiny tropical fruit sector does not bloom as a result of a shortage of growers. A study conducted by Cocal et al. (2017) revealed that out of 42 farmers in the province of Pangasinan, none of them embrace innovative technologies in their farm management Additionally, Mopera (2016) discussed in his paper the substantial post-harvest losses in the Philippine agriculture sector, including the impact of diseases on crop yields and the economic implications for farmers. There is restricted access to high-quality planting materials and R&D activities, inadequate technological adoption, a lack of production standards, and a prevalence of pests and diseases.

In a special release fruit situation report in Davao region facilitated by the Philippine Statistics Authority in 2020, watermelon farming in Region 11, particularly in the municipality of Hagonoy, was included in the top 10 fruit crop production in the region amounting to 1, 233.26 tons for the year 2019. However, watermelon farming in Davao del Sur faces significant challenges due to insect and pest infestations, which lead to substantial reductions in crop yields and economic losses. According to the Philippine Statistics Authority, the region has experienced a decline in fruit crop production, including watermelons, due to various factors such as pests and diseases, particularly in Barangay Sacub. One major challenge is the early detection of viral infection. The complexity of identifying these infections requires technical expertise, which many local farmers lack due to their reliance on traditional farming methods. Common diseases such as purple blotch and leaf blight frequently affect their watermelons, leading to significant crop losses during the harvest season. This situation has resulted in substantial economic setbacks for the farmers in the region.

The researchers developed an android-based watermelon leaf disease detection and remedy using TensorFlow and CNN to enhance the image classification using the sequential model and reduce the aforementioned algorithm's complexity as well as address watermelon growers' problems. The researchers also worked in four classes from 1 crop with two different leaf diseases to recommend basic information, treatment, and control measures based on watermelon leaf images. Offline features make the app accessible in remote areas.

Figure 1 depicts the bird's-eye view of the project. The researchers used two features: (1) capturing of watermelon leaves using a Convolutional Neural Network (CNN); and (2) evaluation of the captured images, including suggestions for potential treatments and preventative measures. The system recommender provides the disease name and treatment; a user can take another leaf sample.

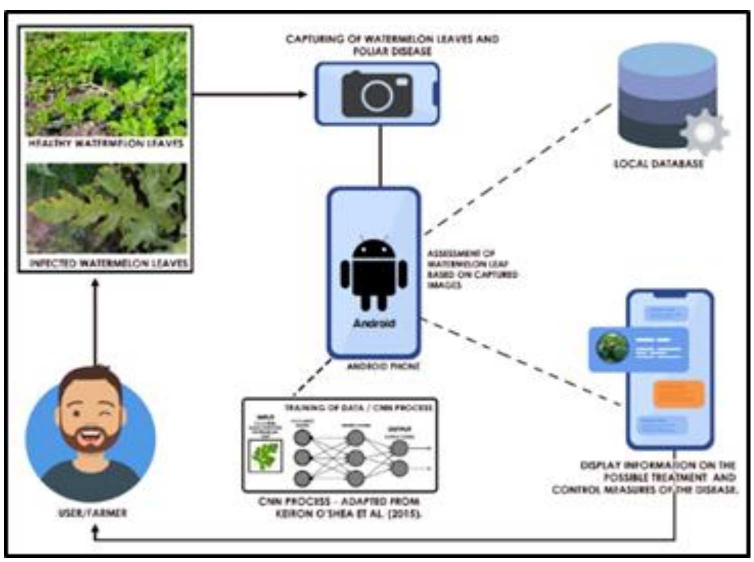

Figure 1. *Conceptual Framework of the Study*

Methods

Distribution of Data Sets

The proponents used 4,800 actual images from a Sweet 16 Watermelon Variety, which is the only thriving variety planted in the locale, in two commonly foliar diseases. Images were manually labeled as datasets to train the model grouped according to four classes, namely, Anthracnose, Downy Mildew, healthy leaves, and unknown. Figure 2 shows the sample images for Anthracnose and Downy Mildew. The size of the images was set to 250x250 pixels and in jpeg format. The datasets followed the splitting of 70:15:15, where 70% consisting of 3,360 images were used to train the model. Moreover, 15% of the images were used as a test image which consists of 720 images, and the remaining 15% was used to further validate the output of the training model which consists of 720 images (Muraina, 2022). Table 1 shows the proper distribution of the datasets; it shows the four attributes used to train the model. Additionally, the images used were validated by a plant pathologist in the college who served as one of the technical experts of this project.

Table 1. Dataset Distribution

Class	Training Data	Test Data	Validation	Total Images
Anthracnose	840	180	180	1,200
Downy Mildew	840	180	180	1,200
*Healthy Leaf	840	180	180	1,200
*Undefined Object	840	180	180	1,200
Total	**3,360**	**720**	**720**	**4,800**

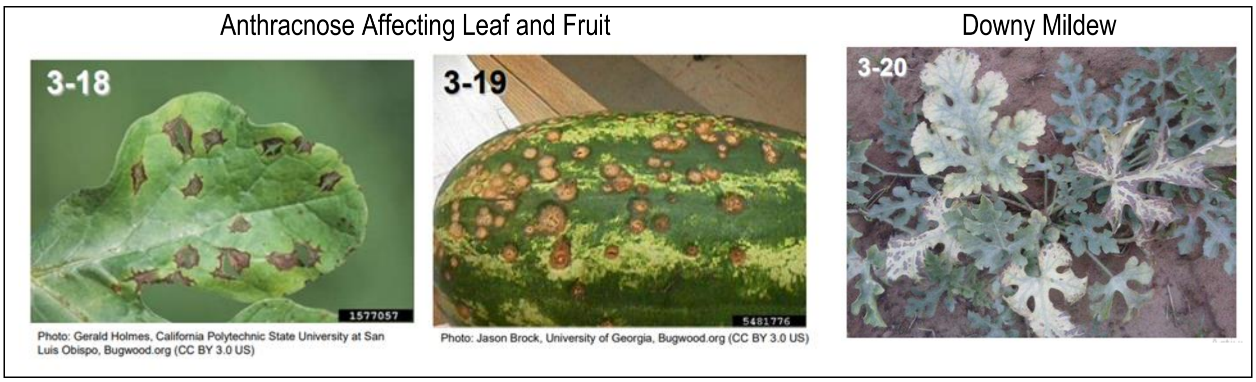

Figure 1. *Sample Dataset of the Study.*

Data Flow Diagram of the Study

To visually represent the actual process that happens behind each output of the application, Figure 2 shows the data flow of the project. It adopts the method of training by Lamrani et al. (2022) where the detection of the presence of a brain tumor in a magnetic resonance imaging (MRI) was used. These two major processes inside the application where the trained model was embedded, as the user captures the image in an onion with suspected disease infection using their smartphones (e.g., capture image), the model will take it as input data which will be fed to the trained model (e.g., prediction and disease detection) and analyze whether or not it is infected with a disease. Once diagnosed as infected, the model will then provide a treatment recommendation to the user.

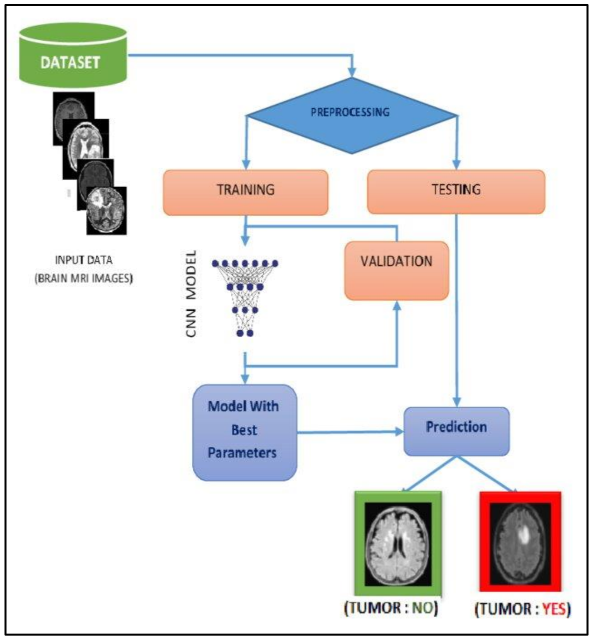

Figure 2. *Process Flow of the Study.*

Keras Hyper-Parameter Configuration

Since Keras is a high-level API built on top of TensorFlow which allows for easy model building, training, and evaluation, hyper-parameters were set in a way that important features of the model were adjusted in order to optimize model performance (Alhazmi, 2023). In the case of learning rate and optimizer, Adam optimizer was used, which was set to its default learning rate of 0.001. *ImageDataGenerator* was created to contain data generators intended for the batch sizes which is set to 32, where input shape or pictures in this case was set to (150, 150, 3), which means the model expects input images of size 150x150 pixels with three color channels (RGB). In training the model, epochs or iterations of randomly selecting images across the four classes in the dataset were set to 30, which means that the model will be trained 30 times using randomly selected pictures among the created and labeled classes. To avoid overfitting the model, the dropout rate was set to 0.5, which means that 50% of the neurons will be dropped during the training phase. The number of Kernel and Filter size is also an integral part when it comes to fine-tuning the hyper-parameters. In this case, the first convolutional layer has 32 filters with a kernel size of (3, 3), the second has 64 filters, and the third has 128 filters.

Testing and Evaluation Procedures

A 5-point Likert psychometric scale was used in the self-constructed survey questionnaire that follows the patterns of ISO/IEC 9126 metrics of selected variables (e.g., functionality, reliability) to be measured in the study. Table 2 illustrates the Likert scale measurement of the aforementioned variables for this project study. Getting the weighted mean of the response allowed the researchers to discover the insights of the respondents which was used to further develop the application. The researchers used the formula to get the mean value of the respondents.

$$\bar{\mathbf{X}} = \frac{\Sigma x}{n}$$

Where,

$\bar{X}$ represents the score

Σx represents the sum of all scores from every evaluator

n represents the total number of evaluators

Table 2. Likert Scale Measurement for Functionality and Reliability

Mean Range	Descriptive Equivalent	Interpretation
4.51 – 5.00	Excellent (E)	The measure outlined in the item is exceptional and delivers all requirements.
3.51 – 4.50	Good (G)	The measure described in the item is satisfactory and fulfills most requirements, however there is potential for improvement.
2.51 – 3.50	Fair (F)	The measure described in the item is acceptable, but there is considerable potential for improvement.
1.51 – 2.50	Poor (P)	The measure described in the item required essential enhancement to fulfill requirements.
1.00 – 1.50	Very Poor (VP)	The measure described in the item requires major modifications in order to fulfill the requirements.

The evaluation scale ranges from one to five, with five being the highest score and one as the lowest. The corresponding denotation of the scores are as follows: 4.51 to 5.00 as “Excellent (E)”, 3.51 to 4.50 as “Good (G)”, 2.51 to 3.50 as “Fair (F)”, 1.51 – 2.50 as “Poor (P), and 1.00 to 1.50 as “Very Poor (VP)”. As a result, the Likert scale served as a tool to assess the extent to which the product or service satisfies user requirements, as well as identify areas that require enhancement.

Distribution of Respondents

As shown in Table 3, there were 19 evaluators for this project from diverse backgrounds, which include random watermelon growers from Purok 2, Sacub, Hagonoy, Davao del Sur. Thus, they were given descriptive survey questionnaires to evaluate the project's functionality and accuracy. Prior to the start of the project, watermelon growers, who were qualified in the inclusion and exclusion criteria, were given consent forms.

Table 3. Distribution of Respondents

Evaluators	Sample Size
Advisory Committee	5
Watermelon Farmers	10
IT Experts	3
Plant Pathologist	1
Total	**19**

Results and Discussion

Keras (CNN) Model Training

Artificial intelligence involves the proper identification of a model to be used under the umbrella of machine learning. Keras architecture was utilized by the researchers since it focused on learning from raw pixel data of the images, without requiring any manual feature engineering or preprocessing. Furthermore, the algorithm carefully examined each image to categorize it according to any problems or diseases that may be present in the dataset that was labeled. Figure 4 shows the result of the training; it illustrates the AI's training accuracy which indicates its learning capability. In other words, as the AI's ability to learn improves, the training loss should decrease, respectively. The trend in the figure indicates that the model is effectively learning from the dataset and that the hyperparameter setup is appropriate.

Thus, the model's confidence rate in recognizing the disease was high. The accuracy of a machine learning model during training increases over epochs (from 0 to 80), with values ranging from 0.75 to 0.99 accuracy. The loss (error) of the model decreases over epochs, fluctuating but showing an overall downward trend. The learning curves highlighted in the figure help assess how well the model performs as it is being trained (Ibrahim, 2024).

The application in this study provides the user with detailed results when a diagnosis was carried out as shown in Figure 3. C. The application provides a confidence percentage as to the type of disease it was able to recognize and treatment recommendations. The recommendation is based on established standard agricultural practices that were validated by the plant pathologist. Figure 3 also provides the other two modules in the application, particularly the application's Home Page, and the camera capture module which allows users to capture images using their smartphones.

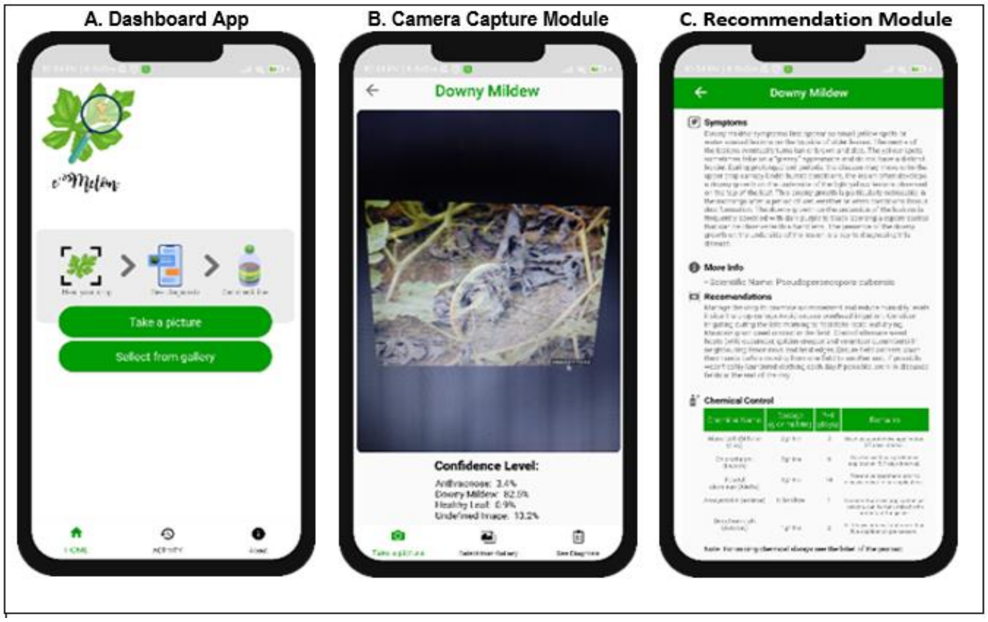

Figure 3. *Application Modules of the Project.*

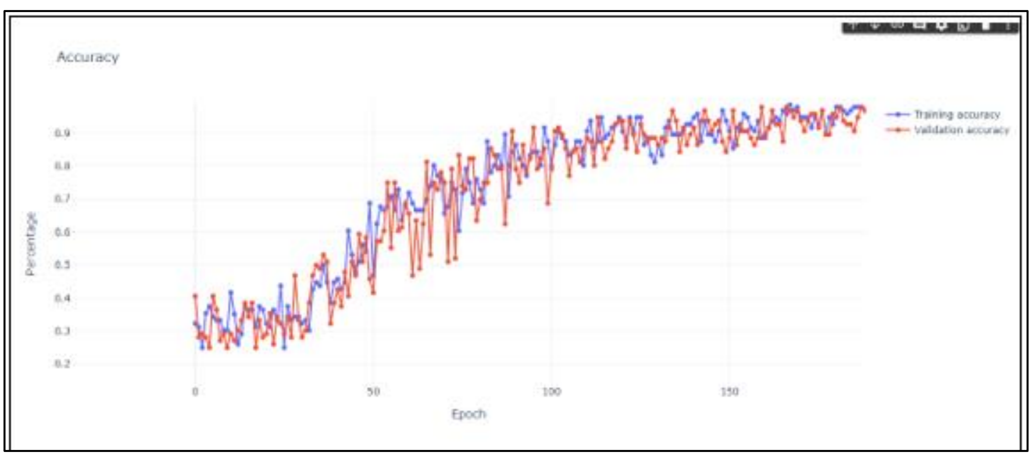

Figure 4. *Model Training Result.*

To further investigate the model's performance, the researchers introduced an additional new set of images which contains a more complex environment setting of subjects for validation. This process was usually carried out in machine learning to ensure that the model can still accurately detect the diseases despite the intricacies of the new input data (Chi et al., 2022). Based on the configured hyperparameters of the algorithm, the result of validation can be seen to be increasing as shown in Figure 5, thus, it is safe to say that the model trained in the dataset used is effective.

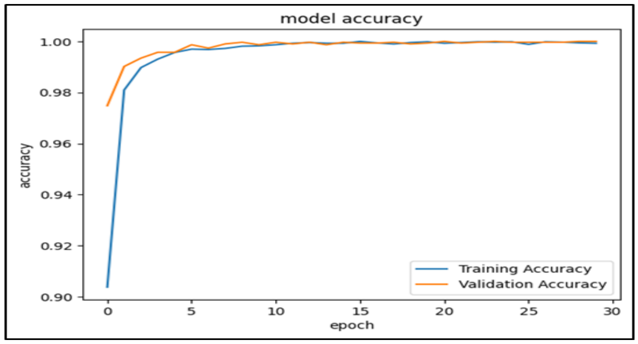

Figure 5. *Model Validation Result.*

Looking into the result of the Confusion Matrix provided in Figure 6 provides a clear picture of the model's strengths and weaknesses in detecting different diseases (Nakib et al., 2023) in watermelon. The Confusion Matrix for the watermelon disease detection model reveals a strong performance in identifying healthy leaf and undefined images, with high true positive rates and minimal false negatives. However, there is some confusion between Anthracnose and Downy Mildew, as well as between Anthracnose and healthy leaf. Specifically, the model correctly identified 833 Anthracnose cases but misclassified 7 as healthy leaf, and it correctly identified 802 Downy Mildew cases but misclassified 38, mostly as Anthracnose. The model accurately identified 836 healthy leaf cases with only 4 misclassifications and 829 undefined images with 11 misclassifications. This highlights the need for improvement in distinguishing between similar disease symptoms to enhance the model's overall accuracy and reliability. Additionally, Figure 7 depicts the classification result of the model for the F1-score, precision, and recall.

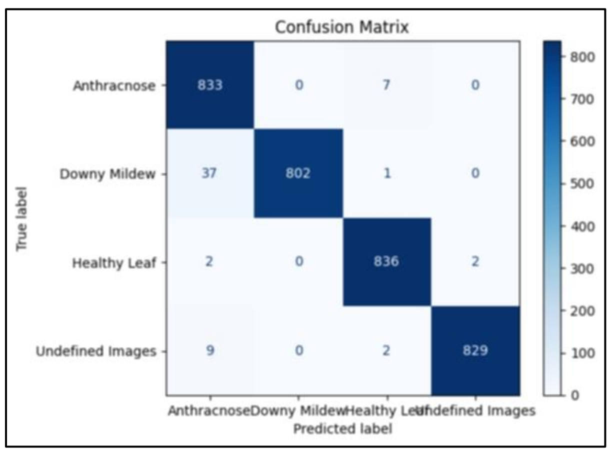

Figure 6. *Confusion Matrix.*

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Classification Report:
                  precision    recall  f1-score   support

     Anthracnose       0.95      0.99      0.97       840
    Downy Mildew       1.00      0.95      0.98       840
    Healthy Leaf       0.99      1.00      0.99       840
Undefined Images       1.00      0.99      0.99       840

        accuracy                           0.98      3360
       macro avg       0.98      0.98      0.98      3360
    weighted avg       0.98      0.98      0.98      3360

F1 Scores for each class:
Anthracnose: 0.97
Downy Mildew: 0.98
Healthy Leaf: 0.99
Undefined Images: 0.99
```

Figure 7. *Model Classification Result.*

The SPIDTECH app, developed by UPLB researchers (Guiam et al., 2021), uses machine learning to identify and monitor crop diseases, providing timely information for farmers. It shows high accuracy in identifying diseases, similar to the watermelon disease detection model, which excels in detecting Downy Mildew with a precision of 0.92 and a recall of 1.00. However, the watermelon model has moderate performance in detecting healthy leaf. SPIDTECH covers a wide range of crops, while the watermelon model focuses on specific diseases like Anthracnose and Downy Mildew. Both models demonstrate the potential of machine learning in agriculture, with SPIDTECH offering broader applications and the watermelon model providing specialized insights.

Experimental Results for Identifying Disease Present in Watermelon

After the trained model was embedded in the mobile application, it was put to actual use by the farmers where it was tasked to recognize diseases in three distinct conditions or levels of infection (i.e., semi-infected, severe infection). An experimental analysis was carried out, where six images with varying levels of infection were used. The level of infection was validated by the plant pathologist. Table 4 shows the result of the application, where it can be seen that varying levels of confidence rate of diagnosis by the application are provided, and the distance (e.g., inches) of capturing was also recorded in this experiment.

Table 5. Experimental Results for Spring Onion Diseases

Experiment No.	Disease Class	Confidence Rate	Distance
1	Anthracnose (Leaf)	95.21%	1
2	Anthracnose (Leaf)	93.11%	2
3	Anthracnose (Leaf)	90.54%	3
1	Anthracnose (Fruit)	94.67%	1
2	Anthracnose (Fruit)	91.23%	2
3	Anthracnose (Fruit)	90.14%	3
1	Downy Mildew	96.00%	1
2	Downy Mildew	95.15%	2
3	Downy Mildew	94.56%	3
1	Healthy	100%	1-3
1	Undefined Object	100%	1-3

` The table indicates that when closer images are taken, results would yield higher confidence rates. This underscores the importance of image quality in recognition systems. By ensuring that images are captured at an optimal distance to maintain clarity and detail, the effectiveness and reliability of this application can be significantly enhanced. Figure 8 shows the list sample recognition output of the classifier. It highlights the confidence rate that the classifier's prediction on the disease it detected and its corresponding class in the labeled datasets.

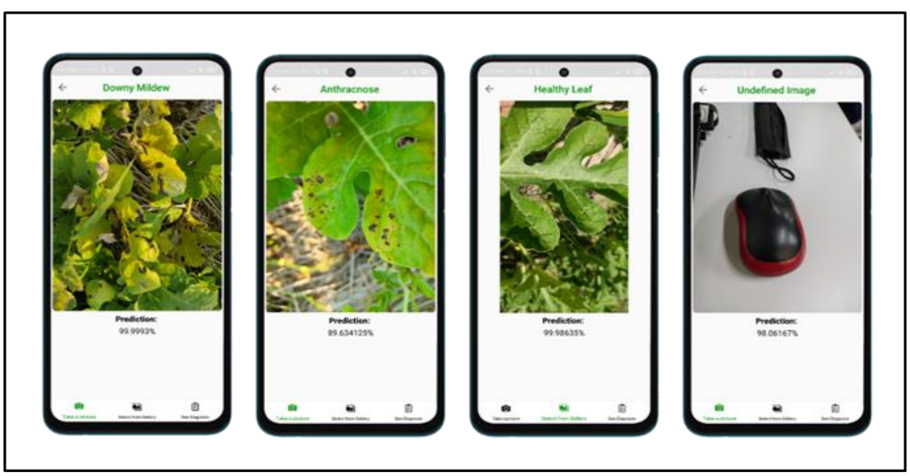

Figure 8. *Classifier Model Training Result.*

Descriptive Ratings the Android Application

To evaluate the functionality, and reliability of the project, a comprehensive testing process was implemented. This involved administering a questionnaire to participants to gather their experiences with the application in accordance with its intended functionalities. Before testing, the researcher conducted an orientation and presentation to ensure participants fully understood the project's objectives and functions. This thorough approach aimed to rigorously assess the project, ensuring it performs optimally in its intended context.

Table 6. Descriptive Ratings from the Respondents in Terms of Functionality

Particulars	Respondents				Mean	Remarks
	IT Experts	*Advisory Committee*	*Onion Farmers*	*Plant Pathologist*		
Capture images of watermelon using a Convolutional Neural Network	5.00	4.90	4.90	5.00	4.95	Excellent
The application can identify a type of disease that is present in watermelon.	4.50	4.00	4.00	4.00	4.12	Good
The application can provide treatment and recommendations based on the disease detected.	4.17	4.50	4.70	4.00	4.34	Good
Average	**4.56**	**4.47**	**4.53**	**4.33**	**4.47**	**Excellent**

Functionality indicates an essential feature of the software, which enables it to perform specific tasks. For example, the first indicator in the survey form indicates the application of watermelon disease. In the survey, the majority of the respondents gave a mean score of 4.47, indicating a high level of agreement that the application is able to deliver its intended functionality.

Table 7. Descriptive Ratings from the Respondents in Terms of Reliability

Particulars	Respondents		Mean	Remarks
	Watermelon Farmers	*Plant Pathologist*		
The module accurately identifies the disease on the Spring Onion.	4.20	4.90	4.55	Excellent
The treatment recommendations are clear and understandable.	4.80	3.90	4.35	Good
The application provides convenient results.	4.40	4.00	4.20	Good
Average	**4.47**	**4.27**	**4.37**	**Good**

In terms of reliability, the strength of the application is the accurate disease detection which means that the application's disease detection capabilities are reliable and effective, and its capabilities to handle tasks resulted to a high score since the application did not crash while they use it. However, still one of the lowest to gain evaluators' approval is the treatment and recommendations and its suggested results which need some revisions. Hence, there is a need to make them clear and concise for the user to easily understand how the treatment will be implemented by non-technical users like novice small-scale farmers.

Table 9. Overall Descriptive Rating from the Respondents in Terms of Functionality and Reliability

Particulars	Mean	Remarks
Functionality	4.47	Good
Reliability	4.37	Good
Total	**4.42**	**Good**

Overall, the results indicate that the application's functionality and reliability were rated as good, with most respondents agreeing that the Android application effectively identifies watermelon diseases and provides appropriate treatment recommendations. Furthermore, a survey by Meshram et al. (2021) highlighted the growing use of deep learning technology in agriculture, with Convolutional Neural Networks (CNNs) significantly enhancing accuracy and learning capabilities. Despite challenges such as dataset creation, testing duration, hardware support, and deployment on small devices, machine learning is gaining popularity in agriculture. Projects like this can help reduce crop losses and offer valuable treatment recommendations to farmers, aiding in maintaining crop health. An application that provides recommendations, chemical treatments, and care tips can greatly support the planting process, leading to better harvests.

Conclusion and Future Works

Based on the result of the study, E'MELON: Android-Based Watermelon Leaf Disease Detection and Remedy Using TensorFlow and CNN, the following are the conclusions:

1. The application can capture watermelon disease (e.g. Anthracnose, Downy Mildew) using CNN. Evaluating the accuracy according to proximity at 1-inch-high leads to a higher confidence rate. In addition, the application gains an average rating of 4.42 with a remark of good. This indicates that one of the factors an AI can generate a high confidence rate is by considering the distance of image captures.
2. The application can identify watermelon diseases in both leaf and fruit occurrence with an average confidence rate of 95.43% mean accuracy rate in experimental activity. However, triangulation of its ability to offer significant treatment support for other diseases is limited since the model was only trained for the two specific diseases that occurred and were observed in the locale.
3. The application can provide recommendations, chemical recommendations, and care tips based on the standards provided by the Agricultural Training Institute (ATI) by the Department of Agriculture, validated by the plant pathologist. In addition, the application gains an average rating of 4.28 with a remark of good. However, the treatments and recommendations given by the application are limited.

Based on the conclusions, the application can successfully capture images using CNN, diagnose diseases, and provide treatment recommendations, and has been successfully compared to the traditional assessment indicating its effectiveness in combating spring onion diseases. However, improvements are needed to enhance its effectiveness. Future researchers in the same field may look into the following recommendations:

1. Selection of appropriately supervised machine learning algorithms such as Sequential Model, MobilenetV2, and YOLOV8 may also be a good first step to consider in addressing a specific problem in image classification and recognition.
2. Additionally, looking into the dataset preparation is highly advised when dealing with supervised machine learning algorithms. This can totally affect the overall performance of the algorithm if the dataset is prepared poorly. Researchers may look into the following in preparing a comprehensive dataset for disease detection and treatment recommendation:
    a) Different disease stages/progression validated by a plant pathologist such as:
        i. *Early Stage:* Initial symptoms such as small spots, discoloration, or slight wilting. These early signs are often subtle and can be challenging to detect.
        ii. *Mid Stage:* More pronounced symptoms, including larger spots, increased discoloration, and more noticeable wilting or curling of leaves.

iii. *Advanced Stage:* Severe symptoms with extensive damage, such as large necrotic areas, significant leaf drop, and extensive wilting or stunting of the plant.

b) Variety of Image in different quality resolution by pixel:

i. *Low Resolution* - 64x64 to 128x128

ii. *Medium Resolution* - 256x256 to 512x512

iii. *High Resolution* - 1024x1024 pixels or higher

3. They may also conduct experimental testing in different smartphones with different camera resolutions to identify what level of resolution can the application work in the best optimum performance.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.