DAVAO MULTIDISCIPLINARY RESEARCH JOURNAL
The Official Research Journal of Davao del Sur State College

Original Article

Android-Based Diamante Max Tomato Maturity Stages Classification Using the VGG-16 Model

Aubrey Estigoy[1], Rhea Mae Perito[1*]
[1] Institute of Computing, Engineering and Technology, Davao del Sur State College, Brgy. Matti, Digos City, Davao del Sur 8002, Philippines
**Corresponding email: rheamae.perito@dssc.edu.ph*

Abstract: The study classified the diamante max tomato maturity stages using the VGG-16 model; thus, an Android application was developed as a portable classifier. Technology-based classification of the maturity stages of tomatoes using the mobile application can lessen the time, provide further information about the six (6) maturity stages of the tomato, and the accuracy rate for the experimental result is 93.6%, indicating that it is comparable to the application. The application was rated by the evaluators and achieved an average mean score of 4.5 for functionality, an average mean score of 4.2 for reliability, and an average mean score of 4.5 for usefulness, which indicates that they were all in agreement that the application was highly working effectively, improves identifying maturity stages of diamante max tomato, and gave the purpose of the study. Furthermore, adding more varieties of tomatoes will increase the application's usability, and the dataset must increase in each maturity stage to provide a more comprehensive view of the data for future researchers. For the application to be utilized as a smart farming solution, the application must be integrated with automated harvesting systems to optimize picking times.

Keywords: android-based application; diamante max tomato; maturity stages classification; vgg-16 model

Introduction

Tomato is the most common and familiar vegetable in everybody's kitchen; thus, it plays a significant role in the food industry (Mputu et al., 2024). Based on the data presented by the Food and Agriculture Organization (FAO) in 2022, the total world tomato production in 2021 has amounted to just over 189.1 million metric tons (*Worldwide (Total Fresh) Tomato Production in 2021 - Tomato News*, 2023). Further, the tomato, or Solanum lycopersicum L., is a significant and extensively cultivated crop in the Philippines (Philippine Statistics Authority, 2019). As a climacteric fruit, tomatoes can be identified by their color, which ranges from green to red as they mature (Bayogan et al., 2022). However, sorting and postharvest grading tomatoes is a heavy task due to their several qualities. It is a crucial process that ensures the quality and safety of the products for

consumers. Traditional methods used for grading tomatoes include a manual approach by trained experts. Manual grading has several challenges, such as the time-consuming process and the significant amount of labor required. Thus, each tomato is individually inspected and sorted by a human expert(Mputu et al., 2024). Das & Yadav (2020) describes the tomato maturity classification as categorizing tomatoes according to their maturity level, which progresses through five stages of ripening: mature green, breaker, light pink, light red, and red. However, human graders' subjective visual interpretation based on experience is vulnerable to environmental influences and prone to inaccuracy (Garcia et al., 2019). Assessing for maturity has become a need for both the food business and farmers. Unripe fruits and vegetables can reduce productivity (Wei et al., 2021).

In recent years, the Convolutional Neural Network (CNN) has gained significant prominence as a leading algorithm in computer vision, primarily due to its advanced techniques for image classification. Its remarkable accuracy of up to 99% in identifying image patterns has drawn significant interest, resulting in it being a frequently deployed algorithm for image classification and enhancing image resolution (Mustafa et al., 2021). The University of Oxford created the convolutional neural network model Visual Geometry Group 16 (VGG16), which won the 2014 ILSVRC object identification competition (Yang et al., 2021). Recently, VGG16 has been employed in several studies involving disease diagnosis and classification for cancer(Albashish et al., 2021; Guan et al., 2019) and pneumonia (Jiang et al., 2021) with accuracy rates of 86.2%, 97.66%, and 89% subsequently. Moreover, it has also been utilized in urban management, which recognizes and classifies garbage, explicitly focusing on domestic garbage with a 75% accuracy rate (Wang et al., 2022).

Furthermore, Huynh et al. (2021) stated that tomato maturity stages are significant in the quality of the product, and over the past decade, research about automated tomato classification has been conducted. The study implemented a methodology to classify the maturity stages of tomatoes using deep transfer learning techniques to be used with sorting systems that employ pre-trained convolutional neural networks, namely ResNet101, VGG19, and VGG16, resulting in the following accuracy rates during the training with 92%, 97%, and 95% respectively. Meanwhile, the models garnered 90%, 94%, and 93% accuracy rates during the testing. Moreover, (Phan et al., 2023) conducted a study on classifying tomato states (ripe, immature, and damaged) using the following models: Res-Net 50, EfficientNet-B0, YOLOv5m, and ResNet 101. Respectively, the models garnered accuracy rates of 98%, 98%, 97%, and 97% during the testing.

However, the studies that were conducted measured only the accuracy rates of the models in classifying the maturity stages and states of tomatoes. No studies employed the development of a portable device that classifies and assesses the maturity stages of tomatoes using the VGG16 on the farm, reducing the burden of manual grading. Therefore,

the researchers developed an android-based diamante max tomato maturity stages classification using the VGG16 model since the model is competitive in the maturity stages assessment. The system was cost-effective, allowing the tomato farmers or growers to have the system with fewer budget concerns. Furthermore, the focus of the study was to classify the maturity stages with an estimated day recommendation to determine when the next stage will occur by capturing the tomato from the vines using the VGG16 model.

Materials and Methods

Application Requirements

System requirements encompass both broad and detailed statements provided by the developer to meet their needs and specifications. This study has identified the application's software, hardware, and dataset requirements to achieve the target functionalities.

Table 1. Software requirements for development.

Software	Specifications
Operating System	Windows 10 or higher
Programming Software	Tensor Flow 2/Android Studio Bumble 2021 or latest
Runtime Environment for Machine Learning	Google Colab Notebook

Tables 1 and 2 present the software tools, environments, and devices needed to develop the mobile application. A computer with Windows 10 OS or higher is recommended, along with installed Tensor Flow 2 API embedded in the Android Studio Bumble 2021. Thus, Google Colab Notebook, as a runtime environment for machine learning, is essential for the training, testing, and validation of the dataset.

Table 2. Hardware requirements for the development.

Laptop	8GB of RAM or higher
Android Phone	4GB ROM or higher 2GB RAM or higher Android 8.1 OS or higher 16px camera or higher
Hardware	Specifications

The researcher collected datasets from the tomato growers' farms of each maturity stage of the tomato used in training the model for classification. Figure 5 shows six maturity stages of the diamante max tomato used in training the model: mature green, breaker, turning, pink, light red, and red.

As shown in Table 3, the preferences of expertise served as the foundation for data collection. As a result, the dataset captured photos of six (6) maturity stages of diamante

max tomato fruit on the farm with the owner's agreement and the farmers' supervision as a dataset foundation. 500 images were captured for every maturity stage, 200 for unidentified things, and 3,200 images were gathered. Those captured images were used for training and testing using the VGG-16 model. Table 4 shows the dataset table of six (6) maturity stages of the Diamante Max tomato used in training the VGG-16 model. Further, proper lighting and illumination were considered using the mobile phone's camera during the dataset collection. The images of the tomato fruits were captured at the farm location during the day, and the researcher ensured that the fruit occupied 70-80% of the space in each image.

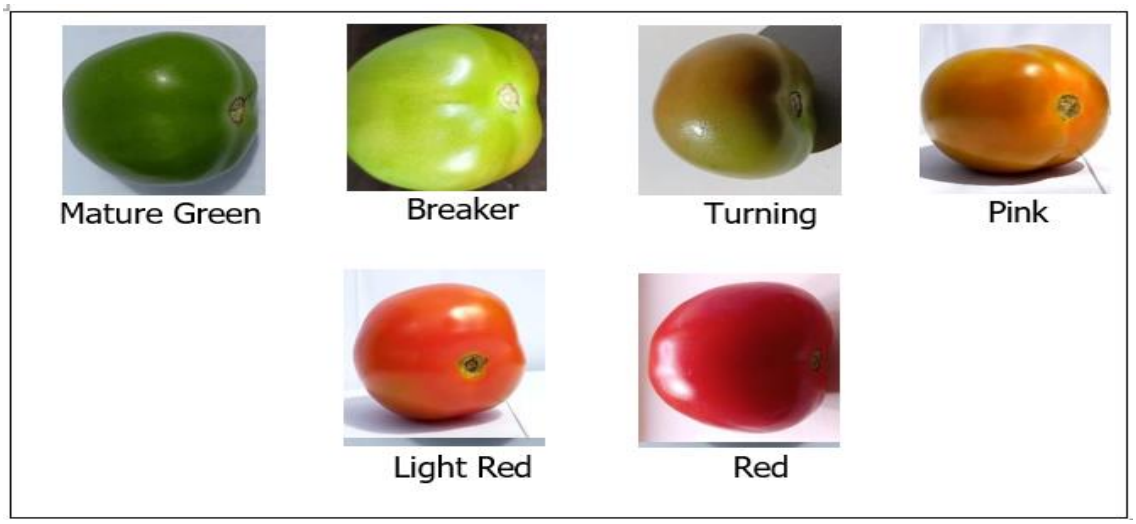

Figure 1. Six (6) maturity stages of diamante max tomato dataset.

Table 3. Number of images for each maturity stage of diamante max tomato.

Maturity Stage	Count
Mature Green	500
Breaker	500
Turning	500
Light Pink	500
Light Red	500
Red	500
Undefined Images	200
TOTAL	3,200

Implementation Plan

Image preprocessing and hyperparameter optimization

After the dataset collection, the images were grouped and labeled according to their diseases or classes and resized into uniform dimensions of 224x224 px, then fed into the VGG-16 model for training. The dataset was divided into 70% for training and 30% for testing before feeding into the model; thus, this splitting of dataset strategy conforms to the relevant works in this focus (Alatawi et al., 2022; Mputu et al., 2024). The manual

hyperparameter tuning approach was used to perform hyperparameter optimization; in this method, the hyperparameter values were manually established by combining hyperparameters. The hyperparameters used in this research are the learning rate (You et al., 2019), batch size (Smith, 2018), and epoch, with the following values of 0.001, 32, and 50 as the most fitted. After the dataset preprocessing and setting of the hyperparameters, the dataset is fed to the VGG16 layers to automatically learn the spatial hierarchies of features, such as edges, textures, and shapes, which are essential for recognizing objects in images.

Model Training and Validation

Statistical model-based machine learning (ML) algorithms learn by creating models with the help of a training dataset. The risk of overfitting, or the possibility that the resulting model follows a particular training dataset too closely to the point that it might collect random data features, is a crucial concern in the model-building process (Burzykowski et al., 2023). In this study, before the VGG16 model was utilized to classify the maturity stages of tomatoes, it was fitted through training and validation using the primarily collected dataset. The VGG-16 model was equipped with pre-trained weights designed for the ImageNet dataset. Next, the feature extraction process was applied to minimize the data duplication within the dataset. The outcome of this was a reduction in the amount of energy required for machine learning and an increase in the speed and efficacy of both the learning and generalization stages of the process.

Additionally, the results generated by the convolutional layers were transformed into a flattened feature vector, which was then connected to a final classification model referred to as a fully connected layer. Moreover, the captured image from the camera will be processed by the classifier, which is the trained VGG-16 model. The classified image will be displayed in the result tab with their percentage or confidence of which maturity stage classification is higher. The higher rate will be the classified maturity stage of the Diamante Max tomato. Figure 2 shows the framework of the VGG-16 model trained with the actual dataset.

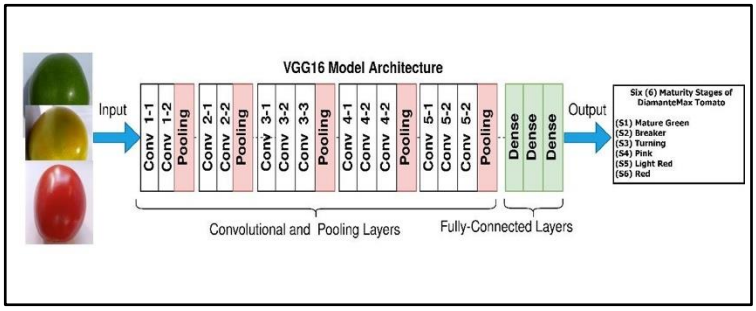

Figure 2. The VGG-16 model trained with the actual dataset.

Model embedding to the application

After the training, the model was exported and integrated into a mobile application. This makes it possible for the model to predict new data even without an internet connection on

the device. The model can now predict and classify tomato maturity stages after it has been integrated into the mobile application.

Capturing the images of the tomato fruits and classifying the maturity stages

Figure 3 shows the capturing and assessing process for classification and the result of the classified Diamante Max tomato according to its color indices using the VGG-16 model with estimated days for the next stage. In Step A, the image is captured, and the classification result for further information about the classified image is displayed. In Step B, viewing information about the Brix level, which corresponds with the classified tomato using the VGG-16 model against experimental results using the tool Brix refractometer and estimated days for the next stage, was established.

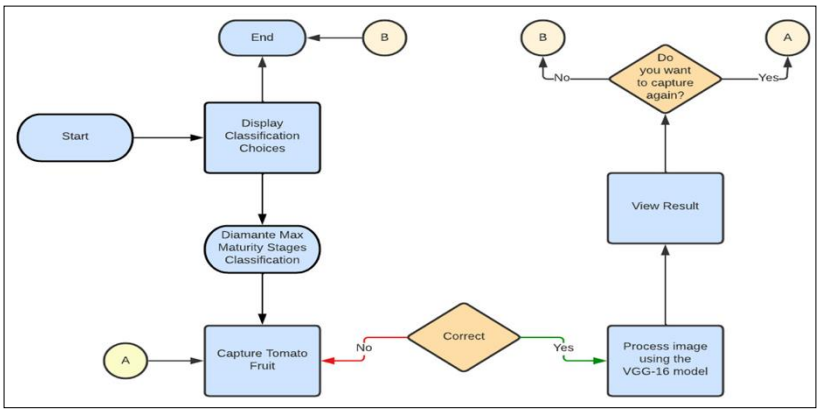

Figure 3. The flowchart on the classification of the tomato maturity stage using the application.

Table 4. Criteria for expert's rating.

Maturity Stage	Description
Mature Green	The surface of the tomato should be 100% Dark and Light Green without any shade of color to be seen.
Breaker	The surface of the tomato should be tannish-yellow, pink, or red color up to 10%.
Turning	More than 10% but not more than 30% of the tomato's surface should change color from green to tannish-yellow, pink, red, or a combination of these colors.
Light Pink	More than 30% but no more than 60% of the tomato's surface should be covered in pink or red. They ripen more quickly than turning tomatoes and are less solid than in the earlier stages.

Light Red	The tomato's surface should be red or pinkish-red, covering more than 60% but not more than 90% of the tomato fruit surface. The pink stage tomatoes are firmer than the light red tomatoes, which are a few days behind reaching fully ripe.
Red	More than 90% of the tomato's surface should become red when the fruit is ripe. Fruits are just the right amount of firm and soft.

As indicated in Table 4, experts utilize their extensive expertise and knowledge to assess fruits based on specific criteria reflected in the study of Cantwell (2010), enabling them to determine the maturity level of fruits during different stages of growth. These stages commonly include mature green, breaker, turning, pink, light red, and red, with each stage being associated with a distinct color shade. During fruit evaluation, experts consider the color transition from the initial green to the final red color, which helps in determining the fruit's maturity level at each stage.

Comparing the accuracy of the application against the experimental result

The comparison of the accuracy of the VGG-16 model was based on the experimental result using a test kit, which is the Brix Refractometer, Expert's Rating, which was the farmers or grower, and color indexes of the tomato fruit by the researcher on the six maturity stages of diamante max tomato. Presented in Table 4 is the instrument or tool used in comparing the accuracy rating of the expert against the Brix Level against the application result for the six maturity stages. The RGB values of each image were extracted as the primary feature which the model considered to familiarize the classes of maturity stages.

Table 5. Tool used in getting the accuracy rating comparison for diamante max tomato maturity stages classification.

Sample Image	RGB Value	Expert's Rating	Brix Level	Application's Accuracy
Mature Green				
Breaker				
Turning				
Light Pink				
Light Red				
Red				
Weighted Mean				

Evaluate the application in terms of functionality, reliability, and usefulness

To determine whether the application was suitable for usage, it was evaluated. As well as the system's usability for users/farmers, data accuracy, and dependability. The system must function correctly and fulfill its mandate for classifying and identifying the tomato's stages of maturity. The evaluation questionnaire was based on the ISO 9126 Software Quality Model standards.

Results and Discussion

Model training and validation results

Presented in Figure 4 is the result of the VGG16 training and validation phase of the study. The model shows promising training accuracy and, thus, shows a fast increase in the initial epochs, indicating that the model is quickly learning the patterns in the training data. Further, the accuracy reached 90%, indicating that the model can learn the relevant features of the tomato maturity stages. On the other hand, during the validation, the accuracy exhibits significant fluctuations and instability through the training process. This suggests that the model performs unreliable or inconsistently on unseen data. Noticeably, there is a gap between the training and validation accuracy, especially during the fluctuations. Potential overfitting is suggested; the model performed very well on the training data but did not generalize well to unseen data.

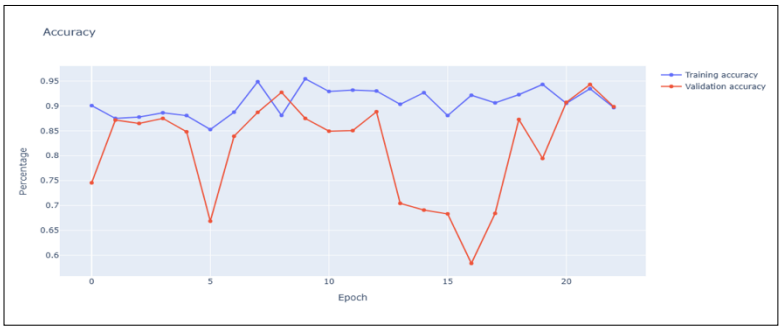

Figure 4. Graph on model training and validation using VGG16.

Figure 5 presents the confusion matrix of the prediction after the training and validation phase. It shows strong diagonal results; thus, it shows a well-performing classification for most maturity stages. For the class breaker, light pink, light red, red, and turning, the model performs exceptionally well, with high counts along the diagonal and only a few misclassifications. This indicates that the model has learned their distinguishing features effectively. The mature green tomatoes have a significant misclassification of 50 out of 150 instances. This suggests that the model struggles to differentiate between the two early stages.

One major issue is the confusion between Breaker and Mature Green. This can result from minor visual parallels or inconsistent labeling of these stages. Examining the pictures in these categories is essential to determining where the uncertainty comes from. A few light pink tomatoes are incorrectly labeled as red or undefinable. This raises the possibility of overlap in these stages' color features. Certain turning tomatoes are incorrectly labeled as Mature Green or Light Red. This might be because the tomato changes color and may mimic other stages during the transitional Turning stage. To address these misclassification issues, it is recommended that data augmentation strategies that introduce color and illumination differences for Breaker and Mature Green be considered to resolve the uncertainty between these stages.

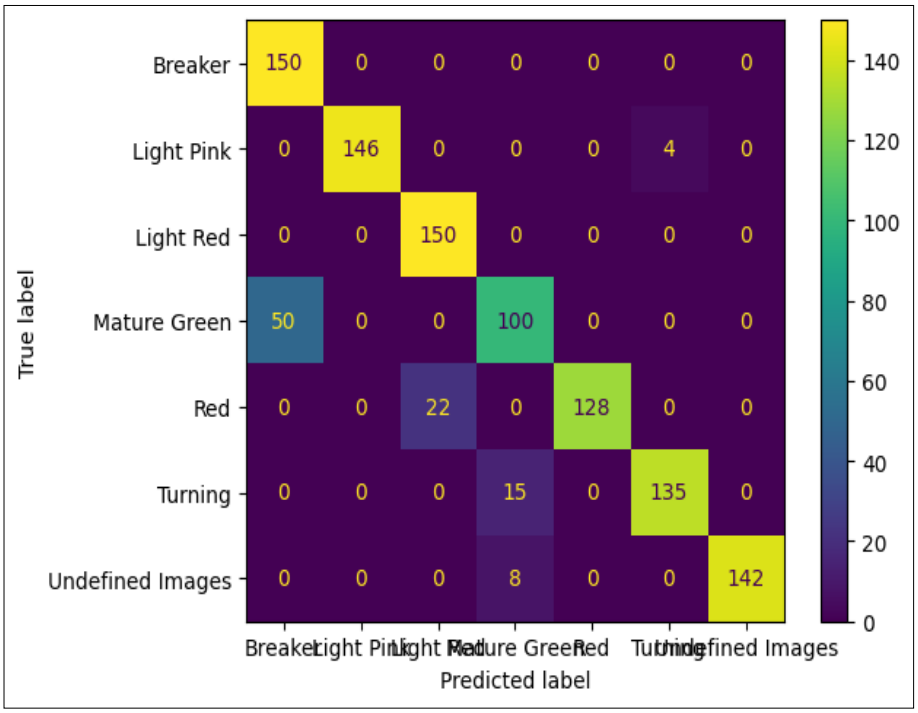

Figure 5. Confusion matrix of the predicted data after training and validation.

Table 6. Classification results using metrics for training and validation.

Accuracy	Precision	Recall	F1-Score
0.91	0.97	0.94	0.95

The model's high accuracy of 91%, as presented in Table 6, suggests that it frequently correctly classifies the tomato maturity stages. This supports the confusion matrix analysis's favorable conclusion. At 97%, the precision is remarkably significant. This indicates that 97% of the time, the model is accurate when it predicts that a tomato belongs to a particular maturation stage. This is especially crucial in situations where incorrectly

identifying a tomato as more mature than it is could result in an early harvest and problems with quality. The recall was likewise excellent, garnering 94%. This shows that the model can identify 94% of all tomatoes that truly belong to a specific maturation stage. High recall is significant when it is essential to avoid missing tomatoes at a particular ripeness stage. At 95%, the F1-score—the harmonic means of recall and precision—is likewise substantial. This indicates that the model is accurate and successful in detecting tomatoes at various stages of maturity since it strikes a fair balance between precision and recall. The high metrics imply that this model may be effectively helpful for automating tomato ripeness classification in real-world situations. It might be included in quality control procedures, sorting lines, or harvesting systems. In conclusion, this model is excellently classifying tomato maturity stages based on its high accuracy, precision, recall, and F1-score. This implies that it may be helpful in the food and agriculture sectors.

Capture and classify the tomato maturity stages through images

Users and farmers can capture tomato fruit images using a mobile application camera. An improved assessment was conducted on the system by image classification utilizing the VGG-16 convolutional neural network model. Users and farmers must choose the Tomato Maturity Tab, as shown in Figure 6, and proceed to the camera button to continue the classification for the capturing process. Also, users can choose from the gallery if there is a captured image stored in the gallery from the mobile device of the users and farmers.

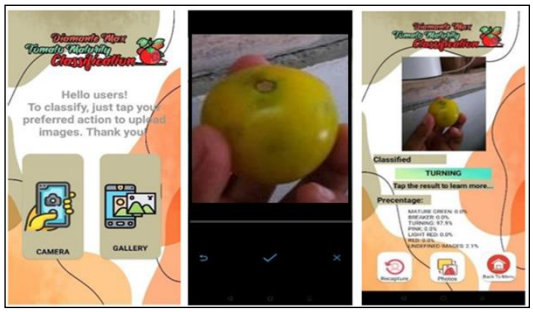

Figure 6. The application's functionality in capturing and classifying the tomato maturity stages.

As shown in Figure 6, the capturing process for classification and the result of the captured image of the Diamante Max tomato using the VGG-16 model are presented. To capture an image of the tomato fruit, proceed to the next step and choose the Camera button. Further, the image that was captured then checks to see if the image that was captured is correct. If it is, proceed to the next step, which you can view and learn more about by clicking the Result Tab among the classified stages and particular information that follows the capturing.

Classify the maturity stage according to color indexes and the number of days of harvest

Capturing and assessing tomato classification is essential for a better understanding of the tomato's development. Figure 7, presented below, demonstrates how this process works,

focusing on the Diamante Max tomato and its color indices, which are analyzed using the VGG-16 model. The figure provides a clear view of the result of the classified Diamante Max tomato, with estimated days for the next stage to occur. To learn more about the classified image, Step 1 instructs the user to tap on the classification result for additional information. In Step 2, the user can swipe the screen back and forth to view information about the Brix level, corresponding to the classified tomato, using the VGG-16 model against experimental results using the tool Brix refractometer. This information is combined with estimated days for the next stage, providing the user an in-depth understanding of the tomato's development.

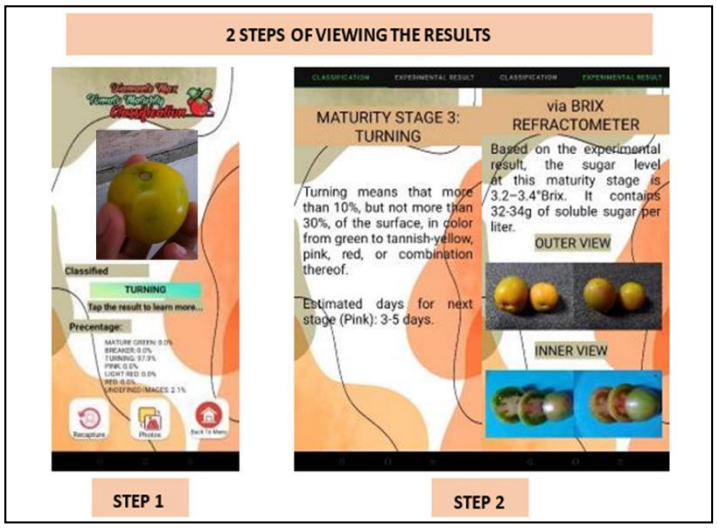

Figure 7. Viewing the results of the classification in the application

Compare the accuracy of the application's classifier against the brix refractometer's result and expert's rating

To evaluate the accuracy of the VGG-16 model for tomato fruit maturity classification, the first metric was the Brix Refractometer, which measures the sugar content of tomatoes. Next, the expert's rating was also included in the evaluation process, which refers to the judgment of farmers or growers. Additionally, the researcher assessed the color indexes of the tomato fruit, including hue, saturation, and value. The experiment was conducted on six different maturity stages of Diamante Max tomato. The comparison of the accuracy of the VGG-16 model was thus determined based on the results obtained from these multiple metrics. Visual evaluations of tomato maturity, which are closely linked to color variations, provide the basis of the expert ratings. Tomatoes change from green to yellow/orange to red as they ripen. The RGB values reflect these color shifts. Therefore, we expect a correlation between the RGB values and the expert ratings. Higher green components (187 and 178) predominate in the RGB values, whereas red and blue are moderate. This is consistent with the appearance of unripe tomatoes. The experts' high 97.66% agreement shows a clear and easily identifiable level. During the breaker stage, there is a shift in the RGB values, with the red component beginning to rise and the green component declining.

This marks the first color shift. Further, in the turning stage, the red component has increased more significantly while the green component has decreased, according to the RGB values. Additionally, yellow tones are starting to emerge. As the correlation shows, as the tomatoes mature, the green component of the RGB values generally decreases while the red component increases. This trend directly reflects the visual color changes associated with ripening.

Additionally, the points rating system corresponds to the level of accuracy on the Likert scale, with the following equivalents: 1-50% a remark of strongly disagree is equal to 1 point rating, 51-65% a remark of disagree is equal to 2 point rating, 66-75% a remark of neither agree nor disagree is equal to 3 point rating, 76-90% a remark of agree is equal to 4 point rating, and 91-100% a remark of strongly agree is equal to 1 point rating. Table 6 compares the accuracy rating for the six maturity stages of diamante max tomato with three sample images.

Table 6. Tool used in getting the accuracy rating comparison for diamante max tomato maturity stages classification.

Sample Image	RGB Value	Expert's Rating	Brix Level	Application's Accuracy	Point Rating
Mature Green	(121,187,117), (124,178,101), (45,65,4)	97.66%	3 °Bx	92%	4.6
Breaker	(98,114,23), (150,160,87), (99,114,21)	94.66%	3.2 °Bx	90.66%	4.6
Turning	(190,191,142), (219,196,160), (189,191,104)	95.66%	3.4-4.0 °Bx	92%	4.3
Light Pink	(240,168,128), (253,175,162), (228,140,92)	95.66%	3.8-4.2 °Bx	95%	5.0
Light Red	(217,30,21), (218,67,38), (224,62,51)	94.66%	3.2 °Bx	90.66%	4.6
Red	(209,26,57), (180,14,34), (126,4,1)	93%	5-6 °Bx	99.33%	5.0
Weighted Mean		**94.82%**		**93.55%**	**4.6**

As shown in Table 6, sample images get their RGB value. They are to be based on the accuracy rating of the experts, brix level, and application model to determine if the experimental result is comparable to the application model. The experimental table with three sample images of each maturity stage of tomato presented results that gained a 94.82% accuracy rating from the experts, a 100% accuracy rating for the Brix Level using the Brix

refractometer tool, and a 93.55% accuracy rating for the application model. Based on the weighted mean score of point ratings, the experimental result of the application model gains a score of 4.0 with a remark of agree, which means that the respondents have acknowledged and believed the objectives have been met. However, it is not entirely attained, and there could be minor issues such as malfunctions, bugs, or unanticipated results. Therefore, the experimental result is comparable to the algorithm used in the application, specifically the VGG-16 model, with minor areas needing improvements.

In the research carried out by Wang et al. (2022), innovative methods such as computer vision and deep learning were applied to the goal of developing a model for an Android-based application that would be capable of recognizing and classifying various types of wild vegetables. Five different CNN models (MobileNetV1, MobileNetV2, VGG-16, Google Net, and InceptionV3) were used to train wild vegetable datasets. MobileNetV2 and VGG-16 had the best recognition accuracy, with 96.92% and 95.31%, respectively. InceptionV3 had the lowest recognition accuracy, with just 89.29%.

Descriptive ratings in terms of functionality, reliability, and usefulness

As specified on the mean ratings for functionality, reliability, and usefulness of the android-based diamante max tomato maturity stages classification, it concluded that the groups of respondents determine the application's effectiveness. The application gained a weighted mean score of 4.5 for functionality, a weighted mean score of 4.2 for reliability, and a weighted mean score of 4.5 for usefulness, as shown in Table 5.

Table 7. Overall descriptive ratings regarding functionality, reliability, and usefulness.

Objectives / Indicators	**Mean**	**Remarks**
Functionality	4.5	Good
Reliability	4.2	Agree
Usefulness	4.5	Agree
Consolidated mean	**4.4**	

Moreover, the application gains a consolidated mean of 4.4 with a remark of Agree which indicates that the application can successfully and effectively perform the functions, meet the standard reliability, and have ease of use and understanding in terms of usefulness for which it was intended. Nevertheless, there are some malfunctions, bugs, and needed improvements of the application itself to consider addressing.

Conclusion and Future Works

Based on the conclusions, the application was able to capture and classify the maturity stages of the tomato fruit, the application is comparable to the experimental results, and the application's functionality, reliability, and usefulness were achieved. As a result, the objectives of the study have been met.

Specifically, the following conclusions can be made: (1) capturing and assessing the images through color indexes, and the number of days of the diamante max tomato gains a mean score of 4.7 from the evaluators with a remark of excellent, which implies that the application can capture and classify the tomato fruit; (2) the application gains a mean score of 4.0 from the evaluators with a remark of agree and the VGG-16 model gains a 93.6% accuracy rating, which implies that the application is comparable to the experimental result; and (3) the evaluation of the application in terms of functionality, reliability, and usefulness gains an overall mean score of 4.4 from the evaluators with a remark of strongly agree which implies that the application was working effectively. Based on the recommendations, the application must add more varieties of tomatoes to classify, add more datasets in each maturity stage, and add additional testing. Furthermore, a database for captured and classified photos to be saved is recommended for future researchers to review and compare the maturity stages identified. Moreover, it is also recommended that market research be conducted to identify the top 10 most commercially relevant tomato varieties in the target region. For the application to be utilized as a smart farming solution, the application must be integrated with automated harvesting systems to optimize picking times.

References

Alatawi, A. A., Alomani, S. M., & Alhawiti, N. I. (2022). *Plant Disease Detection using AI based VGG-16 Model—ProQuest*. https://www.proquest.com/openview/33e6627686425a66f3b93d563d7d0d4d/1?pq-origsite=gscholar&cbl=5444811

Albashish, D., Al-Sayyed, R., Abdullah, A., Ryalat, M. H., & Ahmad Almansour, N. (2021). Deep CNN Model based on VGG16 for Breast Cancer Classification. *2021 International Conference on Information Technology (ICIT)*, 805–810. https://doi.org/10.1109/ICIT52682.2021.9491631

Bayogan, E. R., Secretaria, L., Lequigan, D., & Abad, R. (2022). The use of brick-walled evaporative cooler for storage of tomato. *Journal of Horticultural Sciences*, *17*(1), 190–198. https://doi.org/10.24154/jhs.v17i1.1230

Burzykowski, T., Geubbelmans, M., Rousseau, A.-J., & Valkenborg, D. (2023). Validation of machine learning algorithms. *American Journal of Orthodontics and Dentofacial Orthopedics*, *164*(2), 295–297. https://doi.org/10.1016/j.ajodo.2023.05.007

Das, P., & Yadav, J. P. S. (2020). Automated Tomato Maturity Grading System using CNN. *2020 International Conference on Smart Electronics and Communication (ICOSEC)*, 136–142. https://doi.org/10.1109/ICOSEC49089.2020.9215451

Garcia, M. B., Ambat, S., & Adao, R. T. (2019). Tomayto, Tomahto: A Machine Learning Approach for Tomato Ripening Stage Identification Using Pixel-Based Color Image Classification. *2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, 1–6. https://doi.org/10.1109/HNICEM48295.2019.9072892

Guan, Q., Wang, Y., Ping, B., Li, D., Du, J., Qin, Y., Lu, H., Wan, X., & Xiang, J. (2019). Deep convolutional neural network VGG-16 model for differential diagnosing of papillary thyroid carcinomas in cytological images: A pilot study. *Journal of Cancer*, *10*(20), 4876–4882. https://doi.org/10.7150/jca.28769

Huynh, D. P., Vo, M. V., Dang, N. V., & Truong, T. Q. (2021). Classifying maturity of cherry tomatoes using Deep Transfer Learning techniques. *IOP Conference Series: Materials Science and Engineering*, *1109*(1), 012058. https://doi.org/10.1088/1757-899X/1109/1/012058

Jiang, Z.-P., Liu, Y.-Y., Shao, Z.-E., & Huang, K.-W. (2021). An Improved VGG16 Model for Pneumonia Image Classification. *Applied Sciences*, *11*(23), Article 23. https://doi.org/10.3390/app112311185

Mputu, H. S., Abdel-Mawgood, A., Shimada, A., & Sayed, M. S. (2024). Tomato Quality Classification Based on Transfer Learning Feature Extraction and Machine Learning Algorithm Classifiers. *IEEE Access*, *12*, 8283–8295. IEEE Access. https://doi.org/10.1109/ACCESS.2024.3352745

Phan, Q.-H., Nguyen, V.-T., Lien, C.-H., Duong, T.-P., Hou, M. T.-K., & Le, N.-B. (2023). Classification of Tomato Fruit Using Yolov5 and Convolutional Neural Network Models. *Plants*, *12*(4), Article 4. https://doi.org/10.3390/plants12040790

Smith, L. N. (2018, March 26). *A disciplined approach to neural network hyper-parameters: Part 1 -- learning rate, batch size, momentum, and weight decay*. arXiv.Org. https://arxiv.org/abs/1803.09820v2

Wang, B., Gao, W., & Yang, B. (2022). *Recognition Method and Application of Wild Vegetables based on Lightweight Convolutional Neural Network Model*. https://bit.kuas.edu.tw/~jni/2022/vol7/s2/05.JNI0273_r1.pdf

Wei, M., Wang, H., Ma, T., Ge, Q., Fang, Y., & Sun, X. (2021). Comprehensive Utilization of Thinned Unripe Fruits from Horticultural Crops. *Foods*, *10*(9), Article 9. https://doi.org/10.3390/foods10092043

Worldwide (total fresh) tomato production in 2021—Tomato News. (2023). https://www.tomatonews.com/en/worldwide-total-fresh-tomato-production-in-2021_2_1911.html

Yang, H., Ni, J., Gao, J., Han, Z., & Luan, T. (2021). A novel method for peanut variety identification and classification by Improved VGG16. *Scientific Reports*, *11*(1), 15756. https://doi.org/10.1038/s41598-021-95240-y

You, K., Long, M., Wang, J., & Jordan, M. I. (2019, August 5). *How Does Learning Rate Decay Help Modern Neural Networks?* arXiv.Org. https://arxiv.org/abs/1908.01878v2