CHAPTER I

INTRODUCTION

1.1 Background

Melon (Cucumis melo L.) is one of the most popular tropical fruits in Indonesia because of its sweet taste and high nutritional content. There are various types of melons, including green fleshy melons (honeydew) and orange-fleshed melons (cantaloupe), which are categorized based on the color of their flesh. According to a report from (Hendra, 2024), as many as 926 kg of melons were successfully sold on the Ngrowo Bening fruit picking tour in May 2024. This shows the high consumer interest in melons (Hendra, 2024).

According to research conducted by (Huda et al., 2019), melons, especially the cantaloupe type, are rich in essential nutrients such as vitamin C, vitamin A, potassium, vitamin B6, folic acid, and niacin, all of which are beneficial to human health. The carotenoid content in orange-fleshed melons supports heart health and the immune system, while green-fleshed melons contain vitamin B6 which helps keep bones and teeth strong.

Melon has a wide variety of characteristics, including shape, size, skin and pulp color, texture, aroma, and dissolved solids content, which vary among cultivars such as reticulatus (netted), inodorus (non-netting), and cantalupensis (aromatic). To determine the type of melon, it is often necessary to cut the fruit to observe the color of the flesh, a process that is impractical and can reduce the market value of the fruit. However, the type of melon can be identified by examining the appearance of the skin, although this requires special expertise, which is usually possessed by

certain individuals such as traders, farmers, or seasoned consumers. The problem arises when consumers or others with limited experience cannot distinguish the type of melon just by observing the skin. This often leads to errors in fruit selection, which can ultimately affect consumer satisfaction. In addition, for business operators such as fruit distributors or retailers, misclassification of melon types can result in inventory inaccuracies and reduce distribution efficiency.

To address this problem, the application of Machine Learning (ML) technology offers a potential solution to develop a system that classifies melons. This approach also considers the limitations of manual sorting, which is often limited by certain physical factors or conditions, thus reducing the effectiveness and efficiency of the sorting process. Various Machine Learning techniques can be used for classification, one of which is the Convolutional Neural Network (CNN) method.

CNNs are a type of deep learning neural network designed to recognize, classify, and detect objects in images. CNNs eliminate the need for manual feature extraction by learning directly from the input object. This method is particularly effective in applications such as visual recognition, medical image analysis, image segmentation, and natural language processing, as it can automatically handle various two-dimensional shapes without human intervention. Its main advantage lies in its ability to detect important elements in images efficiently and reliably (Taye, 2023).

The success of Convolutional Neural Networks (CNNs) in various studies is shown through their ability to improve classification accuracy and prediction efficiency in various fields.(Bharadiya, 2021) highlights that CNNs excel in image

classification through data efficiency, transfer learning, and high scalability, allowing pre-trained models to improve accuracy even with limited data. (Saragih & Emanuel, 2021) showed that in the classification of banana ripeness levels, the MobileNet V2 model achieved an accuracy of 96.18%, higher than NASNetMobile which obtained 90.84%, thanks to transfer learning and fine-tuning techniques. Meanwhile, CNN combined with hyperspectral imaging was able to estimate the ripening time of Hass avocados with an average error of only 1.17 days, more accurate than traditional classification methods (Raj et al., 2021) In addition, CNN also managed to improve the image classification accuracy of the Stone-Scissors-Paper game from 97.66% to 99% through hyperparameter optimization and the use of higher epoch values, which contributed to reducing overfitting and improving model accuracy (Nur et al., 2022) With these various achievements, CNN has proven to be an effective and adaptive deep learning method in various applications of image classification and computer vision-based prediction.

In addition to CNN, there are other architectures that offer their own advantages, namely the VGG architecture. The VGG architecture has the advantage of simplicity and structured depth, with the consistent use of 3×3 small convolution layers to capture features from low to high levels. This model is very effective for transfer learning because it has been trained on large datasets such as ImageNet. In addition, VGG is easy to implement, compatible with GPUs, and capable of providing accurate results in image classification.

Although the standard CNN architecture has been proven to be effective, in this Research a custom CNN was used that was specifically designed to adapt to the characteristics of the dataset used. Custom CNN allows adjustment of the

number of layers, filters, as well as regulatory techniques such as dropouts to optimize model performance. In addition, the Research also compared the performance of Custom CNN with VGG16, one of the pre-trained models known to be reliable in image classification thanks to its architectural depth.

The success of the VGG 16 architecture in various studies is shown through its ability to classify images with high accuracy in various research objects. In the research (Hindarto et al., 2023) VGG16 achieved 96.28% accuracy in insect classification, demonstrating its effectiveness in feature extraction and automatic species identification, although VGG19 has a higher accuracy, namely 97.07%. Meanwhile, the research (Putri & Al Maki, 2024) proves the success of VGG16 in the classification of pneumonia by integrating Genetic Algorithm (GA) and Deep Convolutional Generative Adversarial Networks (DCGANs), which increases accuracy from 89.50% to 95.50% and F1-Score from 87.50% to 94.75%, making it more reliable in detecting pneumonia from X-ray images. In addition, (Angelina & Ulfitria, 2024) research shows the superiority of VGG16 in skin cancer classification, with an accuracy of 83.75%, higher than other models such as ResNet50 and VGG19, and has a balance between accuracy, precision, and recall in detecting malignant and benign skin lesions. Overall, these studies prove that VGG16 is a reliable and flexible deep learning model for various image classification tasks, although its performance can be improved with further data optimization and augmentation techniques.

However, high accuracy alone is not enough for practical implementation, especially on devices with limited computing power. Complex architectures like VGG16 often require large storage and heavy computation. Therefore, this

Research not only focuses on accuracy but also explores the trade-off between performance and efficiency by comparing VGG16 (Transfer Learning) with a lightweight Custom CNN architecture designed from scratch.

Another common problem in using digital images for classification is when users capture images in different ways. According to (Xiao et al., 2023)when collecting images in the field, conditions are not always perfect. This is because people capture images from different distances and angles, which causes the images to vary significantly. This variation causes a problem called domain shift, which occurs because objects in the image are not the same size. Therefore, in addition to ensuring the model is good at classifying objects, this Research also tested its performance at various zoom levels, such as 1.5x and 2.5x. This was done to ensure the model can perform well in real-life situations where conditions are constantly changing.

Based on these findings, this Research aims to develop a technology-based solution to handle melon classification based on skin image using the Convolutional Neural Network (CNN) method and the help of VGG architecture as an additional optional architecture as a comparison in this research.

The system will operate automatically, without the need for fruit cutting or relying on individual subjective experience. This solution is expected to improve accuracy in melon classification and support distribution efficiency in Indonesia's agricultural industry. Therefore, this Research will be conducted with the title, "Classification of Melon Based on Skin Image Using Convolutional Neural Network (CNN)". This research is expected to contribute to a new approach to more effective classification of melons.

1.2 Problem Identification

Based on the background of the problem, the following are the results of the identification of the research problem:

1.2.1 Development of a CNN Model for Melon Classification

Nowadays, manual identification of melon types is usually done by cutting the fruit to observe the color of the flesh, which is not only time-consuming but also reduces the market value of the fruit. Therefore, an automated method is needed to identify the type of melon based solely on the image of the skin, providing a more practical and efficient solution. However, to achieve this, the development of artificial intelligence models, especially using Convolutional Neural Networks (CNNs), which are very effective in processing and recognizing patterns in visual images, is needed.

1.2.2 Evaluation of CNN Model Accuracy in Melon Classification

After the development of the CNN model, the next challenge is to determine how effective the model is in classifying melon types based on skin imagery. Although CNNs are known for their effectiveness in image processing, the accuracy of the model still depends on a variety of factors, such as image quality, augmentation techniques, and the complexity of the model's architecture. Therefore, a thorough evaluation is needed to measure the accuracy of the CNN model in distinguishing between green melons and orange melons based on skin images. This evaluation is essential to ensure that the developed model can be applied practically and accurately in real-world scenarios.

1.3 Problem Limitations

This Research focuses on the classification of melons based on skin image using Convolutional Neural Networks (CNNs). The following are some of the problem constraints that are determined to focus the scope of this research:

1.3.1 Melon Condition

The condition of the melon used as data by the researcher is a melon that is not rotten, meaning the skin is fresh and free from defects or animal bites. Specifically, this Research uses two common commercial varieties found in the local market: 'Sky Rocket Melon' representing the Green Melon (Honeydew) class, and 'Rock Melon' representing the Orange Melon (Cantaloupe) class with limited dataset.

1.3.2 Lighting

The data collection carried out by the researcher was carried out using a personal mobile phone that had a shortcoming in data quality. Including the lighting in each data. To ensure consistent training, the dataset was collected under controlled daylight conditions, avoiding extreme backlight or shadows, although natural variations in intensity were unavoidable.

1.3.3 Image Acquisition Scale

The Research focuses on evaluating model performance across different acquisition scales. The training data represents standard capturing distance, while testing data introduces closer zoom variations to simulate user behavior in focusing on skin texture.

1.3.4 Evaluation Result

The evaluation metrics focused on accuracy to measure classification performance, as well as computational efficiency (training time and model size) to assess practical feasibility. Accuracy was chosen because it provides a direct picture of how well the model can correctly classify images of green and orange melons. In addition to accuracy, losses are also observed to ensure the model has good generalizations. Evaluation is carried out on the validation data to avoid overfitting. For a more detailed analysis, the confusion matrix is used to find out the number of true positive/false negative predictions, thus providing a deeper understanding of the model's performance.

1.4 Research Questions

The research questions in this Research are as follows:

a. How to develop a Custom CNN architecture that is effective for melon classification with limited datasets?

b. How does the performance of the Custom CNN compare to the pre-trained VGG16 architecture in terms of accuracy?

c. Which architecture offers the best trade-off between performance and computational efficiency for practical implementation?

1.5 Research Objectives

The objectives of this research are as follows:

a. To compile a specific dataset of green and orange melon skin images that reflects real-world variations.

b. To develop and train two CNN models (Custom CNN and VGG16) for binary classification of melons.

c. To analyze and compare the accuracy and computational efficiency of both models to determine the most suitable solution.

1.6 Research Benefit

The benefits of this Research are as follows:

1.6.1 Theoretical Benefits

This research will enrich the development of Convolutional Neural Network (CNN) applications in the field of image processing (computer vision), especially for fruit classification based on skin imagery. Using CNN, this Research has the potential to deepen the understanding of deep learning applications in object classification not only based on color or shape but also on skin patterns and textures.

1.6.2 Practical Benefits

a. Providing an Automated and Accurate Solution for Melon Type Identification Without Cutting the Fruit.

By developing a CNN model that can classify melon types based solely on skin image, this research can help consumers, traders, and industry players in distinguishing melon types faster, easier, and more accurately without the need to cut the fruit. This will increase consumer comfort and satisfaction in choosing melons that suit their needs.

b. Efficiency in Distribution and Inventory Management

For agricultural industry players, especially fruit distributors and retailers, this research can increase efficiency in managing melon inventory and distribution.

With the automatic classification system, the process of sorting melons by type can be carried out quickly and accurately, reducing errors and improving operational efficiency.

1.6.3 Social Benefits

a. Improving Consumer Accessibility and Knowledge

This research can provide consumers with a better understanding of how to visually distinguish different types of melons, even without prior experience. This increases consumer knowledge, leads to more informed purchasing decisions, and increases their satisfaction.

b. Potential for Solution Dissemination on a Larger Scale

The technology developed in this Research can be widely adopted in the market and agricultural industry, potentially extending to other types of tropical fruits, given its efficiency and ease of application in various aspects of the food industry.