BAB 1 INTRODUCTION

Farmers play a crucial role in tomato production to meet both local and global market demands. Tomatoes are not only an economically significant horticultural crop but also a staple in agricultural trade, with global tomato production exceeding 180 million metric tons annually. Market research shows that quality standards, particularly ripeness, are critical to determining the market value of fresh produce, as nearly 40% of post-harvest losses are attributed to quality issues, including misclassification of ripeness [1]. Tomatoes, like other perishable fruits, have distinct ripening stages that affect shelf life and consumer appeal, making accurate and timely ripeness assessment essential.

Visual indicators such as color are primary markers for ripeness in tomatoes, as well as other crops like watermelons and dates [2]. However, data from tomato farmers reveals that manually assessing ripeness is both time-consuming and resource-intensive. Leveraging technologies such as machine learning can enhance productivity and alleviate the workload for farmers. Through deep learning, farmers can also improve the quality of their harvests by ensuring accurate ripeness detection. Optimizing harvest timing based on precise classification not only improves produce quality but also enhances profitability, aligning with market expectations and increasing revenue potential [3]. Developing automated systems for ripeness classification is essential to support the agricultural sector's adaptation to quality-sensitive global market demands [4].

Previous research has demonstrated progress in using deep learning for detecting and classifying fruit ripeness from RGB images. Study conducted by Plants (2023), the ResNet-50, EfficientNet-B0, Yolov5m, and ResNet-101 networks achieved testing accuracies of 98%, 98%, 97%, and 97%, respectively [5]. ResNet-152 efficiently detects tomato ripeness by learning visual features like color and texture. It improves accuracy and supports automation in food processing but relies on visual data and requires significant computational power [6]. This study uses a larger dataset of tomatoes compared to previous studies. The number of tomato images in this study's dataset is 7,224, categorized into four conditions: Unripe, Ripe, Old, and Damaged. Studies on models such as Xception have demonstrated that modifications like depthwise separable convolution can significantly enhance accuracy and efficiency compared to earlier architectures like VGG16 and ResNet152 [7].

This study evaluates a deep learning approach using the Inception-V3 architecture for classifying tomato ripeness from RGB images. Inception-V3 was selected for its strong performance in handling visual complexity, computational efficiency, and deep feature extraction capabilities, particularly when compared to other architectures such as ResNet and VGG. While ResNet models are known for their residual connections that ease gradient flow in very deep networks, they typically come with higher computational demands. Meanwhile, VGG networks, although effective in feature extraction, require substantially larger parameters, which can impact efficiency in real-time agricultural applications. The primary distinction of this research from previous studies lies in modifications to Inception-V3 parameters, including adjustments to the number of epochs, optimizer, learning rate, and activation function, tailored to optimize the model's accuracy and runtime efficiency. This research aims to improve classification success rates and accuracy, contributing a deeper understanding of Inception-V3's performance and applicability in tomato ripeness classification.