UTM UNIVERSITI TEKNOLOGI MALAYSIA

FACULTY OF COMPUTING
UTM Johor Bahru

**SECJ3563 - COMPUTATIONAL INTELLIGENCE**

**MINI PROJECT REPORT**

# TITLE: Classification According to Fruit Maturity

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## Introduction

With an annual production of over 180 million tons over the previous seven years, tomatoes stand out as one of the most consumed vegetables. Plants are essential to meeting the world's food demands. Because of their hardness, long shelf life, and ability to continue ripening after harvest, tomatoes are usually picked commercially at the mature ripening stage, satisfying consumer preferences for fresh produce. The need to preserve product maturity across the supply chain and transportation operations is another factor that motivated this choice. The use of technology in agriculture, especially for crop detection and classification, is becoming more and more well-known in academic circles. Crop monitoring and harvesting are becoming more precise and effective with the use of deep learning and image processing tools. These operations have been completely transformed by the introduction of robotic technologies, which have improved crop maturity and output, optimised harvesting techniques, and decreased labour costs—all of which have enhanced production profits (Khan et al., 2023).

This mini project's utilisation of the Tomato Maturity Detection and Quality Grading Dataset allows for the classification of tomato maturity. The dataset contains the Tomato Maturity Detection Dataset and Tomato Quality Grading Dataset, those 2 datasets have their own 2 directories which include the augment dataset and the original dataset. For the Tomato Maturity Detection Dataset, the inside augment dataset and original dataset have immature and mature images. The Augment dataset may be images from the original data set, processed through a process called data augmentation so that the deep learning model can learn to better handle the multiple factors that may affect the appearance of a tomato. However in this mini project, we would be only focused on the discussion of tomato maturity, instead of both maturity and quality and the deep learning algorithm will be used as an approach to classify the maturity of tomatoes (Tomato Maturity Detection and Quality Grading , 2023).

## Objectives

The aims of this mini project regarding Classification According to Fruit Maturity using Deep Learning Techniques are as follows:

1. To develop a machine learning model capable of classifying fruits based on the maturity stages
2. To investigate the feasibility of utilising deep learning algorithms in the classification of fruit maturity.
3. To assess the effectiveness of deep learning algorithms using various numbers of learning rates and momentum rates.

## Problem Background

For producers and retailers alike, it is critical to promptly determine the maturity indices of fruits and vegetables since these indices not only specify the ideal harvesting period but also impact sales strategies and consumer contentment. When fruits are harvested at the proper maturity stage, uniform ripening and high maturity are guaranteed; early harvesting results in uneven ripening and low quality, resulting in decreased market value. Therefore, the best practices for harvest maturity are important to the storage and commercial viability of fruits. It is impossible to overestimate the importance of accurately determining maturity indices because it has an immediate impact on the quality and market value of fruits and vegetables. Therefore, the creation of automated systems that identify crops according to their maturation phases using cutting-edge machine-learning algorithms appears to be a viable solution (Kumar et al., 2023).

Zhu et al. (2021) and Bhargava and Bansal (2021) have published survey articles focusing on the use of machine learning and computer vision techniques for the grading of various fruits and vegetables. When given enough training datasets, deep learning models, such as CNN, have demonstrated exceptional performance in picture classification tasks when compared to traditional machine learning methods. CNN models eliminate the need for feature extraction and increase performance through hyper-parameter adjustment.

## Related Research

The application of deep learning (DL) techniques, particularly convolutional neural networks (CNN), has significantly advanced the field of fruit maturation classification. Ashtiani et al. (2021) highlight the evolution brought about by CNNs, noting their success in image classification and recognition tasks. Various methods have been proposed for automatic fruit maturity inspection and grading, addressing problems across different areas of the agriculture sector.

Halstead et al. (2018) developed a robotic vision system utilising the Faster R-CNN technique to classify sweet pepper ripeness into three categories: unripe, partially ripe, and ripe. Ge et al. (2019) employed the Mask Region-CNN model to detect and classify different ripening levels of strawberries (raw, pink and ripe) in farm conditions. Liu et al. (2019) introduced a modified densely-connected convolutional network (DenseNet) for detecting the maturity of tomatoes in complex images. Their improved DenseNet outperformed other framework such as ResNet, DenseNet, and single-shot detector (SSD) in terms of detection rate

Moreover, transfer training has been effectively applied in tomato maturity classification. Das et al. (2021) utilised a pre-trained AlexNet network for automatic grading based on the colour stages of tomatoes (green, yellow, and red). Their model achieved 100% accuracy, surpassing the performance of other deep learning and machine learning techniques, and offered a cost-effective solution for tomato maturity grading.

These advancements demonstrate the potential of CNNs and their derivatives in enhancing the precision and efficiency of fruit maturity classification. Our project aims to build on this foundation by focusing on the classification of tomatoes by maturity, leveraging state-of-the art deep learning techniques to achieve accurate and reliable results

## Methodology

The algorithm that will be implemented for this mini project is the Deep Learning Algorithm. Deep learning-based models—particularly convolutional neural networks (CNN)—for classification and detection have been proposed more commonly as a result of advances in deep learning and high-computational hardware technology. These models have demonstrated strong performance on a variety of crops (Krizhevsky et al., 2012). Based on Deep Artificial Neural Networks, Deep Learning is a subfield of machine learning. It has shown to be an effective solution for a variety of image processing problems related to remote sensing, including UAV-based imagery. For many image processing and computer vision-based applications, CNN is the state-of-the-art deep learning technique among the many available methods (Bouguettaya et al., 2022).

As this mini project will focus on classily the maturity of the tomatoes, large volumes of tomato images can be processed by using a deep learning algorithm. The texture, color, and size of various crop types—which change depending on the health and growth stages—have a significant impact on the deep learning model's performance (Bouguettaya et al., 2022). As shown below, the

The procedure of this project will have the following steps:

**Data Collection:** Gather Tomato Maturity Detection Dataset, including images of tomatoes at various maturity stages.

**Data Preprocessing:** Adjust the dataset to ensure an equal number of samples for each class. This step prevents the model from being biased towards the majority class and enhances its performance in recognizing all classes equally.

**Splitting Data:** Divide the dataset into training (85%) and testing (15%) sets to evaluate the model's performance.

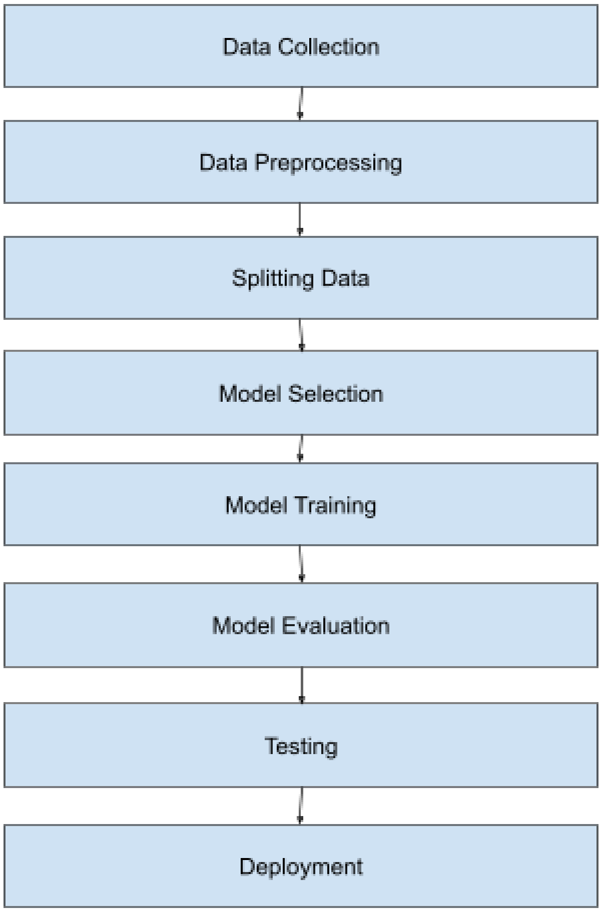
**Model Selection:** Convolutional Neural Networks (CNNs) are utilized due to their effectiveness in image classification tasks and compatibility with Google's Teachable Machine platform.

**Model Training:** Train the selected model using the training dataset. Adjust parameters such as epoch, batch size, and learning rate during training to optimize model performance and accuracy.

**Model Evaluation:** Evaluate the trained model using the testing dataset. Monitor metrics such as accuracy, and loss per epoch to assess its effectiveness.

**Testing:** Test the model's ability to classify tomato maturity stages using new, unseen data.

**Deployment:** Deploy the trained model into the Teachable Machine website for practical use, ensuring it can accurately classify tomatoes in real-time scenarios.

<table>
<tr><th>Workflow</th><th>Pseudocode</th></tr>
<tr><td>


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1. Start
2. Data Collection:
    a. Collect tomato images dataset for maturity detection.
3. Data Preprocessing:
    a. Preprocess dataset to balance samples across maturity stages.
4. Splitting Data:
    a. Split the dataset into 85% training and 15% testing sets.
5. Model Selection:
    a. Select Convolutional Neural Networks (CNNs) for image classification.
6. Model Training:
    a. Train CNN model with adjusted epoch, batch size, and learning rate.
7. Model Evaluation:
    a. Evaluate model performance using testing dataset metrics.
8. Testing:
    a. Test model on new data to classify maturity.
9. Deployment:
    a. Deploy trained model on Teachable Machine for real-time tomato classification.
10. End

</td></tr>
</table>

## Result and Discussion

A. Data Acquisition

In this project, the type of data that will be focusing and collected is image data. The images used in this project were predominantly sourced from the Kaggle website. Each tomato image was categorized into one of two types: Mature and Immature. A total of 500 sample images were collected for each type of tomato to build the machine-learning model dataset. Figure 4.1 shows our collected dataset.

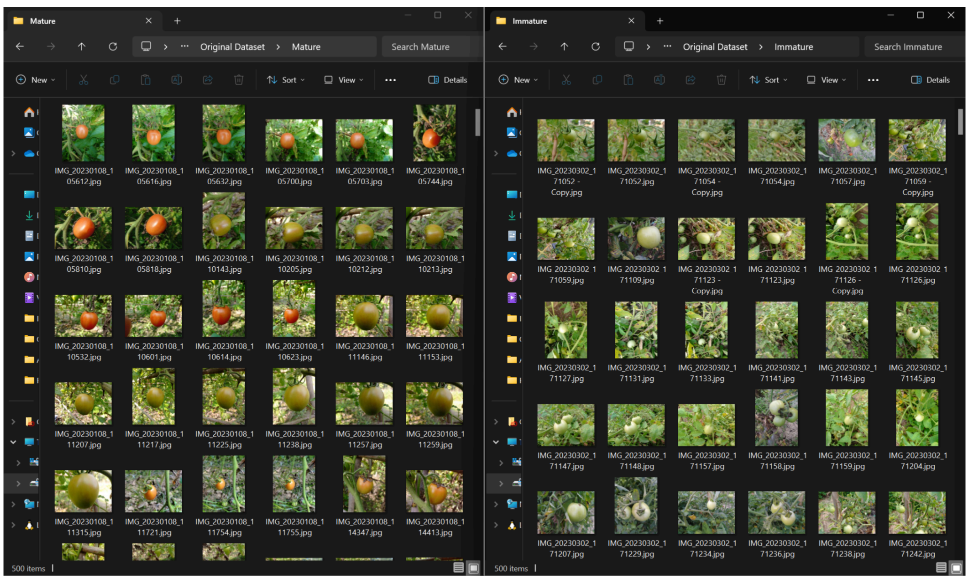



Figure 4.1 Collected Dataset

B. Training Data

The collected dataset will be utilized to develop a machine-learning model through data training. This procedure will be executed using Google's Teachable Machine website, which is integrated into a web browser. Click on the "Get Started" button and choose a data training method to initiate the process. For this specific project, image identification is being employed. The sample images can be directly uploaded from the computer on the image project page. Since the image samples have already been downloaded from the internet, they can be uploaded from the computer folder. The website provides default CNN parameters such as epochs, batch size, and learning rate. In this case, we have set 50 epochs, a batch size of 16, and a learning rate of 0.001. Upon completion of the training, the machine learning model can be downloaded by clicking on the "Export Model" button.

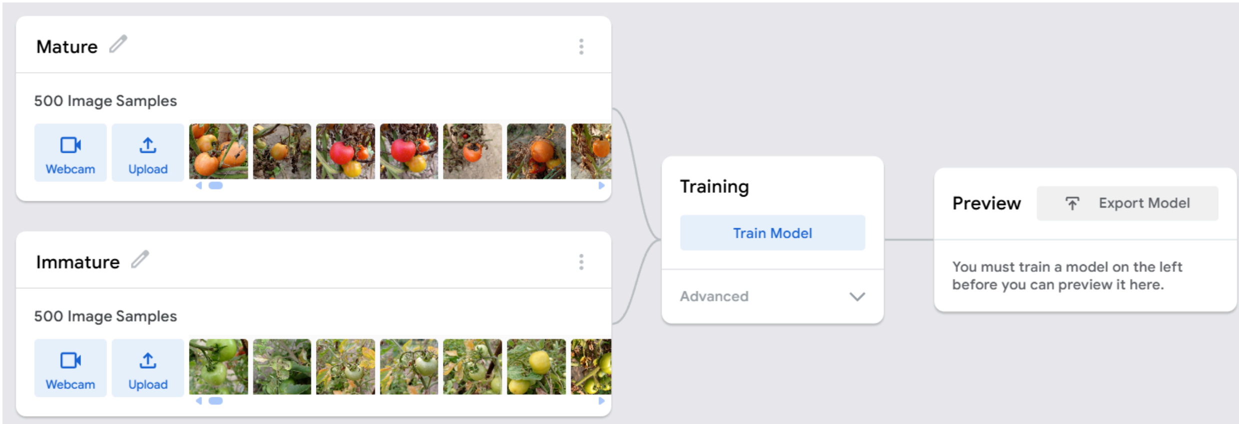



Figure 4.2 Model Training Page

C. Model Testing

This specific stage is implemented throughout the data training phase of the machine learning model. The testing is conducted by modifying the CNN parameters while generating the training data. Within this stage, a total of 5 distinct parameters are examined during the model testing process.

Table 4.1 Modeling Parameters

| **Variable** | **Parameter 1** | **Parameter 2** | **Parameter 3** | **Parameter 4** | **Parameter 5** | **Parameter 6** |
|---|---|---|---|---|---|---|
| Epoch | 2 | 5 | 10 | 20 | 50 | 50 |
| Batch Size | 16 | 16 | 16 | 16 | 16 | 16 |
| Learning Rate | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0005 |

Table 4.2 Accuracy Performance

| **Class** | **Parameter 1** | **Parameter 2** | **Parameter 3** | **Parameter 4** | **Parameter 5** | **Parameter 6** |
|---|---|---|---|---|---|---|
| Mature | 0.98 | 0.99 | 0.99 | 0.99 | 0.99 | 1.00 |
| Immature | 0.97 | 0.98 | 0.97 | 1.00 | 0.99 | 1.00 |

D. Model Evaluation

Based on the average accuracy performance measured in the table, it showcases that the parameter 6 will provide higher accuracy in classifying the varieties of the tomato. Not only the accuracy table, Google's Teachable Machine also provided the charts for the confusion matrix, accuracy per epoch, and loss per epoch. The figures below will show the output of charts supplied by Teachable Machine.

Figure 4.3 Model Accuracy

Accuracy per class

| CLASS | ACCURACY | # SAMPLES |
|---|---|---|
| Mature | 1.00 | 75 |
| Immature | 1.00 | 75 |

Figure 4.4 Model Confusion Matrix

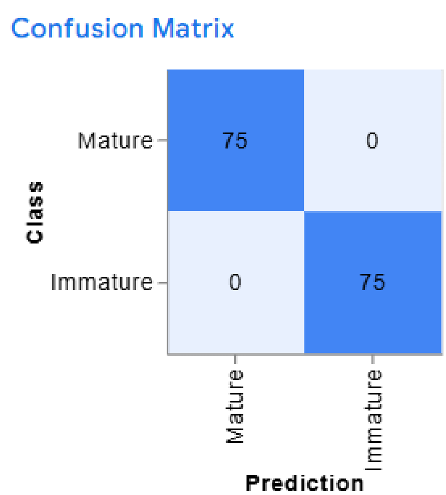



Figure 4.4 Model Accuracy per Epoch

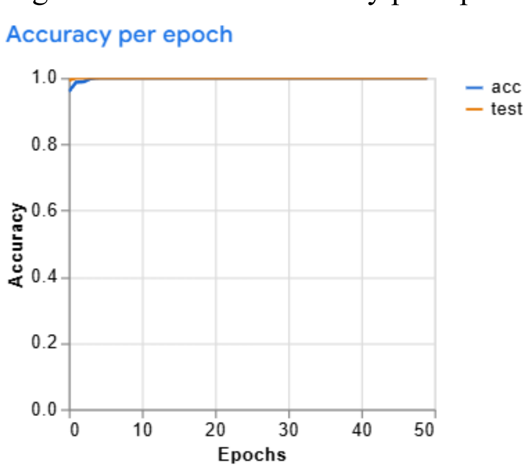
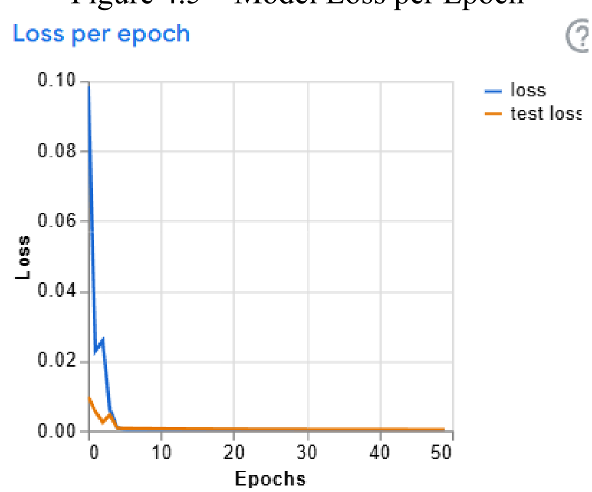



Figure 4.5 Model Loss per Epoch



## Conclusion

This study has successfully demonstrated the application of deep learning techniques, specifically Convolutional Neural Networks (CNNs), in classifying tomato maturity using Google's Teachable Machine platform. The research objectives were met through the development of a robust machine-learning model capable of multi-class classification for tomato maturity stages.

Key findings from this study include:

1. The effectiveness of CNNs in extracting relevant features from tomato images for accurate classification.
2. The importance of data preprocessing and balanced datasets in improving model performance.
3. The impact of adjusting learning parameters such as epoch count, batch size, and learning rate on model accuracy.

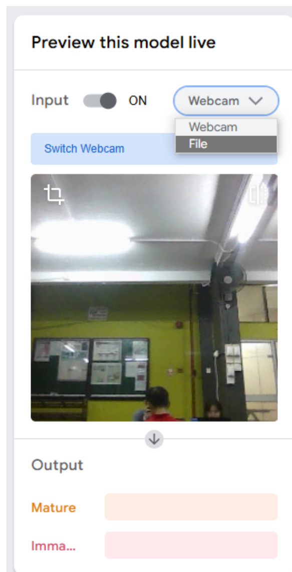
The best-performing model achieved high accuracy across all classes (Mature: 1.00, Immature: 1.00) with 50 epochs, a batch size of 16, and a learning rate of 0.0005. This demonstrates the potential of deep learning in automating and enhancing tomato maturity assessment processes.

The implementation of this model through Google's Teachable Machine platform showcases the accessibility of advanced machine-learning techniques for practical agricultural applications. This approach can significantly streamline maturity control processes in the tomato industry, potentially leading to improved efficiency in supply chain management and enhanced consumer satisfaction.

In conclusion, this study contributes to the growing body of research on AI-driven agricultural practices, offering a promising solution for automated tomato maturity assessment that can be readily adopted by producers and retailers in the global market.

## User Manual

1. **Accessing the Website**: Open your web browser and navigate to the [Teachable Machine Model](Teachable Machine Model).
2. **Enabling Camera Access**:
   - Upon entering the website, you will be prompted to allow access to your camera. Click "Allow" to proceed.
   - If you prefer not to use the camera, you can switch to file upload mode by clicking on the "Webcam" drop-down list, and switch to “File”.



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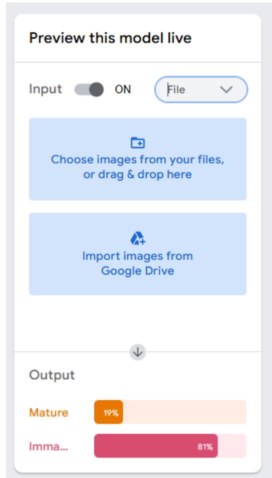
3. **Using the Camera**
   a. **Positioning the Tomato:**
      i. Place the tomato in front of your camera. Ensure the tomato is well-lit and positioned centrally in the camera view.
   b. **Capturing the Image:**
      i. The application will automatically capture an image once it detects a tomato in the camera view.
      ii. Wait for the analysis to complete. The detection result will be displayed on the screen.
4. **Uploading an Image**
   a. **Switching to File Upload:**
      i. Click on the either choose image or import image upload the file.




ii. Select the tomato image file from your computer.

b. **Uploading and Analyzing:**

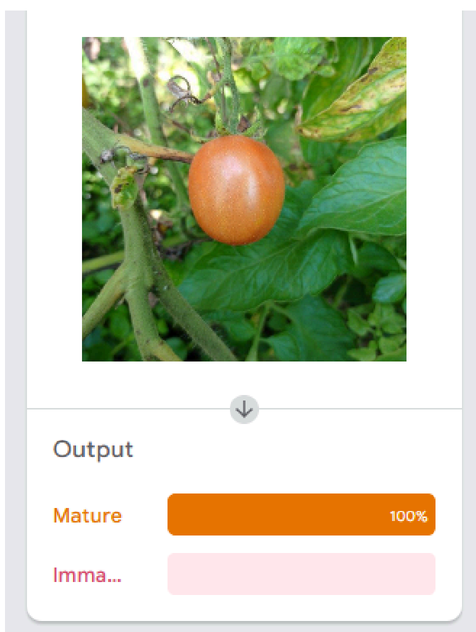
i. After selecting the image, click "Open" or "Upload" to initiate the analysis.

ii. Wait for the application to process the image. The detection result will be displayed once complete.

5. **Interpreting the Results**

a. The application will classify the tomato based on its maturity stage (e.g., immature, mature)

b. Results will be displayed with labels indicating the classification outcome.



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