CLASSIFICATION ACCORDING TO FRUIT MATURITY

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ABSTRACT

Tomatoes are a fundamental component of the agricultural industry worldwide, with significant production and consumption levels. To meet market standards and satisfy consumers, it is essential to conduct accurate maturity assessments. This study goes beyond simply categorizing tomatoes based on their maturity through the utilization of deep learning methods. By making use of the Tomato Maturity Detection and Quality Grading Dataset, convolutional neural networks (CNNs) are applied to analyze images of tomatoes, extracting key features that are crucial for distinguishing between different maturity stages. The main objectives of this research include the development of a robust machine learning model capable of multi-class classification, the exploration of deep learning techniques in this specific context, and the evaluation of model performance by adjusting learning and momentum rates. The methodology involves data preprocessing, the selection of algorithms with a focus on CNNs, model training using a Teachable Machine platform, and systematic implementation with continuous monitoring. Through the automation of the assessment process, this project aims to enhance tomato maturity control, improve agricultural practices, and ensure consumer satisfaction in markets worldwide.

1. Introduction

Tomatoes play a crucial role in the global agricultural industry, as their high production and widespread consumer demand necessitate rigorous maturity assessments throughout the supply chain. The need to preserve product maturity across the supply chain and transportation operations is another factor that motivated this choice (Khan et al., 2023). 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, optimized harvesting techniques, and decreased labor costs—all of which have enhanced production profits (Khan et al., 2023).

The advent of Artificial Intelligence (AI), particularly machine learning (ML), has revolutionized various industries by enabling systems to analyze data, identify patterns, and automate decision-making processes. Google's Teachable Machine offers a user-friendly web-based platform that simplifies the creation of ML models, including object detection (Google, 2017).

This study focuses on the implementation of machine learning using Google's Teachable Machine. The main objectives are as follows:

1. Develop a robust machine learning model that can accurately classify tomatoes into different maturity stages.
2. Investigate the effectiveness of convolutional neural networks (CNNs) within Google's Teachable Machine to enhance the precision and efficiency of tomato maturity assessment.

By leveraging deep learning techniques and employing rigorous data preprocessing, this research aims to optimize agricultural practices, streamline supply chain management, and enhance consumer satisfaction on a global scale.

2. Background

The precise determination of maturity indices in fruits and vegetables is essential for producers and retailers alike. These indices determine the ideal harvesting time, impacting not only the quality of the product but also its market value and consumer satisfaction. Fruits harvested at the correct maturity stage ensure consistent ripening and maintain high quality, while premature harvesting results in uneven ripening and reduced marketability.

Automated systems utilizing advanced machine-learning algorithms present a promising solution for simplifying the identification of crop maturation stages. This technology not only enhances accuracy but also boosts efficiency in agricultural processes and supply chain management. Recent research by Kumar et al. (2023) highlights the significant impact of machine learning on optimizing harvest maturity practices, thereby enhancing the storage longevity and commercial viability of agricultural produce.

Scholars like Zhu et al. (2021) and Bhargava and Bansal (2021) have delved into the use of machine learning and computer vision techniques for the grading and classification of fruits and vegetables. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown superior performance in image classification tasks compared to traditional methods. CNNs excel in extracting features and optimizing parameters, making them well-suited for accurately categorizing fruits and vegetables based on their visual attributes.

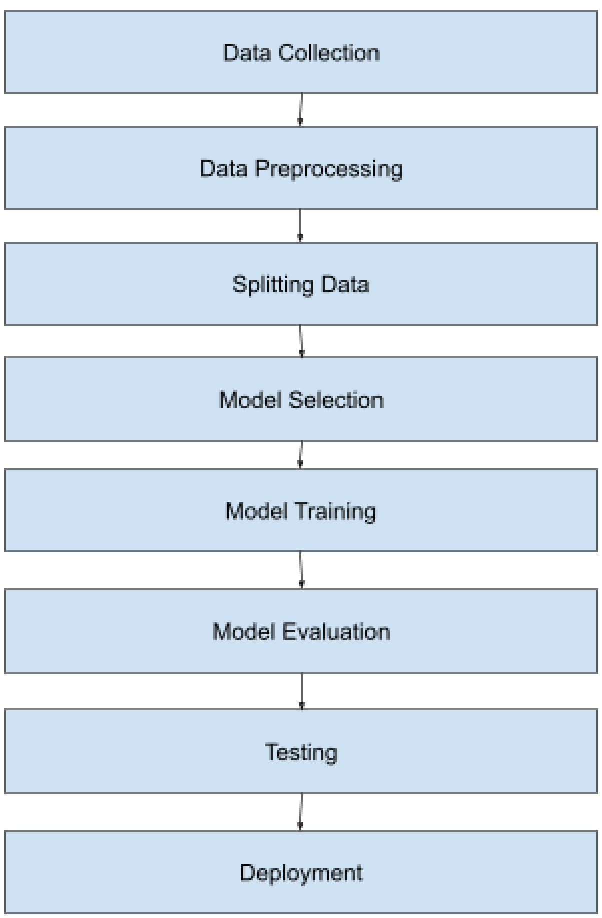
As the agricultural industry continues to evolve, the integration of machine learning technologies holds promise for revolutionizing maturity assessment processes. This report investigates the application of these technologies specifically in enhancing the classification of tomato maturity stages, aiming to optimize agricultural practices and meet the demands of global markets effectively.

3. 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 classify the maturity of the tomatoes, large volumes of tomato images can be processed by using a deep learning algorithm. The texture, colour, 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).

The procedure of this project will have the following steps:

<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:

</td></tr>
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	a. Evaluate model performance using testing dataset metrics. 8. Testing: a. Test model on new data to classify maturity. 9. Deployment: a. Deploy a trained model on Teachable Machine for real-time tomato classification. 10. End

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.

3.1. Convolutional Neural Networks (CNN) in Teachable Machine

Convolutional Neural Networks (CNNs) have revolutionized the field of image recognition and classification by leveraging their capability to autonomously acquire hierarchical representations from raw pixel data. In the context of tomato maturity assessment, CNNs play a crucial role in extracting meaningful features from tomato images, enabling the classification of maturity stages.

Overview of CNN Architecture

The architecture of CNNs encompasses various layers, including convolutional layers, pooling layers, and fully connected layers. These layers work together to progressively develop hierarchical representations of the input data. Convolutional layers utilize filters to extract features such as edges, textures, and patterns from the input image. Pooling layers reduce the spatial dimensions of the feature maps, while fully connected layers integrate these features for final classification.

Integration with Teachable Machine

Google's Teachable Machine offers a user-friendly platform for creating machine learning models, including CNNs, without requiring extensive programming knowledge. The platform simplifies the training process by enabling users to upload datasets, categorize classes, and directly train models through a web-based interface. Key functionalities include:

- Data Upload and Labeling: Users upload tomato images categorized by maturity stages (e.g., immature, mature). Each image is labeled accordingly to facilitate supervised learning.

- Model Training: Teachable Machine allows for the customization of CNN architecture parameters such as the number of epochs, batch size, and learning rate. Training involves iterative adjustments to these parameters to optimize model performance.

- Real-Time Testing and Deployment: Once trained, the CNN model can be tested in real-time to classify new tomato images based on their maturity. The trained model can be deployed for practical applications, such as automated maturity control in agricultural settings.

The utilization of Convolutional Neural Networks (CNNs) within Teachable Machine provides a user-friendly experience due to its intuitive interface and efficient feature extraction abilities. These characteristics accelerate the process of developing and implementing models for accurate evaluation of tomato maturity..

4. 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.

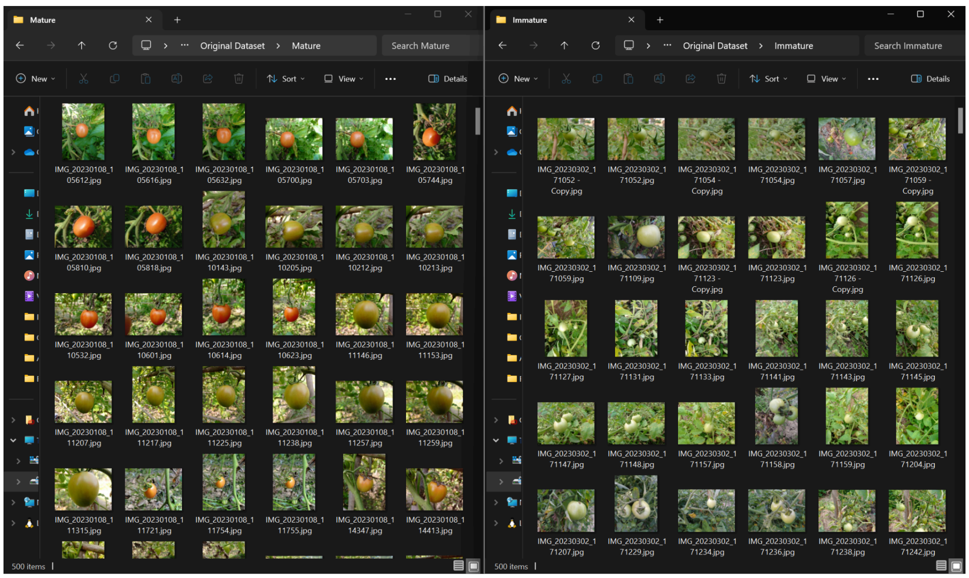


Figure 4.1 Collected Dataset

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.

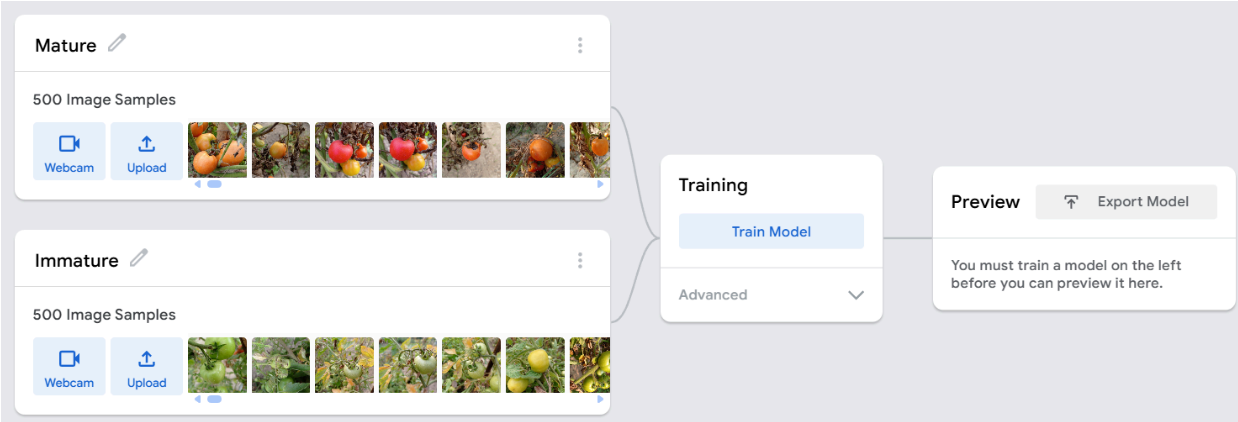


Figure 4.2 Model Training Page

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

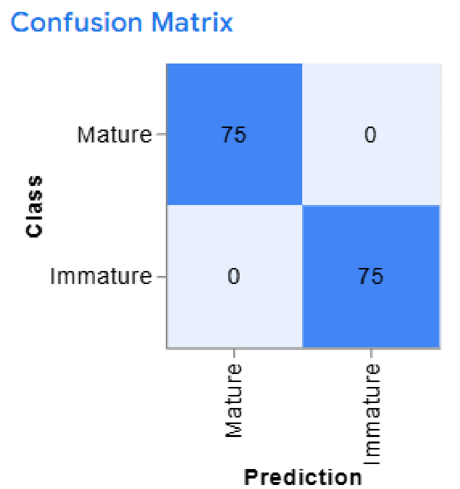


Figure 4.4 Model Accuracy per Epoch

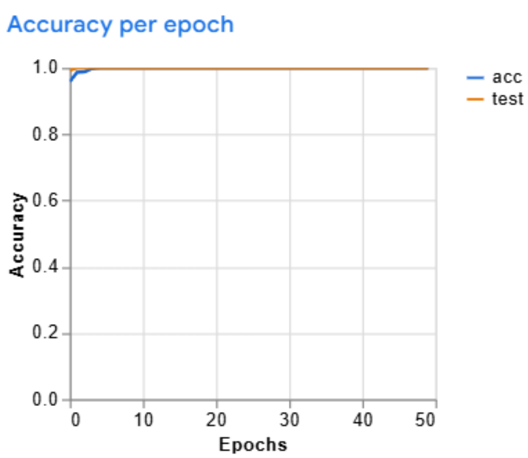
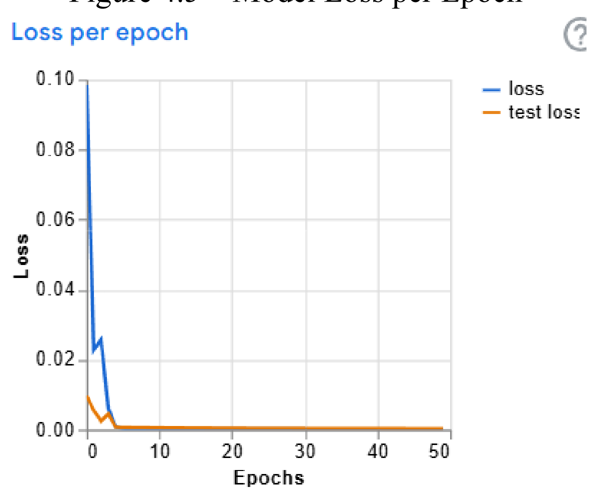


Figure 4.5 Model Loss per Epoch



5. 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.

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