# Tomato Maturity Assessment: Using Convolutional Neural Networks and Image Processing-Based Domain Knowledge

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**Abstract –** This study explores the use of Convolutional Neural Networks (CNN) and image processing techniques to automate the assessment of tomato maturity, classifying tomatoes as either “ripe” or “unripe.” Traditional manual methods for determining ripeness are subjective and labor-intensive, often resulting in inconsistencies due to environmental variables like lighting and background variations. A CNN model was developed and trained using an augmented dataset with diverse preprocessing steps, including background removal, color space conversion, and image resizing. The model achieved an overall classification accuracy of 95.52%, outperforming traditional methods such as Support Vector Machines (SVM) and decision trees in comparative analyses. Key metrics precision, recall, and F1 score confirmed the model’s robustness in identifying ripeness stages, with verification studies on independent data sets further demonstrating its generalizability. This research highlights the potential of CNN-based maturity assessment in enhancing efficiency in agricultural practices, especially for stakeholders in the tomato supply chain. Recommendations include expanding the dataset for broader environmental conditions and developing a mobile application for practical, field-based usage.

**Keywords –** Tomato Maturity, Convolutional Neural Networks, Image Processing, Automated Ripeness Assessment.

## 1 Introduction

In the Philippines, the coffee industry has been fraught with history and current issues Tomatoes are a vital agricultural product in the Philippines, contributing significantly to both the local economy and food supply. The Philippine Statistics Authority (2019) reported that tomato production in the country reached 95.3% thousand metric tons in early 2019 alone, reflecting the crop's economic importance. The ability to accurately assess tomato maturity is critical, as ripeness directly influences quality, consumer preference, and market value. Farmers and distributors often depend on manual visual assessments to determine tomato ripeness, a process prone to inconsistencies due to subjective judgment and environmental variables, such as lighting and background noise [1]-[2]. Additionally, tomatoes are frequently harvested at an immature “green” stage for better transportability, although consumer preference generally favors “red” ripe tomatoes, which complicates the assessment process further [3]-[4].

The limitations of manual maturity assessment have driven the exploration of automated approaches in recent years, with Convolutional Neural Networks (CNNs) and image processing technologies emerging as promising solutions. CNNs, a class of deep learning algorithms known for their accuracy in image classification tasks, have found applications across various domains, including agriculture, where they excel in quality control and maturity assessment of fruits and vegetables [5]-[6]. Machine learning and computer vision techniques, such as CNNs, address key challenges in traditional ripeness grading by providing objective and consistent classification, reducing the need for labor-intensive manual inspection [7]-[8].

Tomato maturity assessment, however, presents unique challenges. Variations in lighting, background complexity, and the inherent differences in tomato size and color require robust preprocessing methods and large, diverse datasets to prevent model overfitting and ensure reliability in diverse environmental conditions [9]-[10]. This study addresses these challenges by developing a CNN-based model specifically tailored to tomato maturity assessment, integrating image preprocessing techniques such as background removal, color space conversion, and resizing to standardize input images. Additionally, data augmentation techniques, including rotation, flipping, and brightness adjustments, are employed to enhance model robustness and adaptability, enabling the model to generalize effectively across varied conditions [11]-[12].

This research aims to design and validate a CNN model that can accurately classify tomatoes as “ripe” or “unripe,” with the potential to outperform traditional classification methods such as Support Vector Machines (SVM) and decision trees [13]-[14]. By providing an efficient, objective, and scalable solution for tomato maturity assessment, this study contributes to the growing body of research on artificial intelligence applications in agriculture, with practical implications for farmers, distributors, and consumers alike. Successful implementation of this technology could significantly improve efficiency and consistency in agricultural quality control, offering a reliable tool for tomato harvesting and quality grading.

## 2 Related Studies

Advances in image processing and deep learning have reshaped agriculture, especially in fruit quality assessment and maturity classification. Automated systems utilizing these technologies reduce labor and increase consistency in quality control, which is essential for products like tomatoes. The use of Convolutional Neural Networks (CNNs) has become increasingly prevalent in agriculture due to their success in complex image-based classification tasks. Studies show that CNNs, combined with robust image preprocessing techniques, can reliably classify fruits based on visual characteristics such as color, shape, and size [7]-[15].

### 2.1 Fruit Quality Assessment

Automated fruit grading methods, including CNNs and digital image processing, address the limitations of manual grading, which is time-intensive and can vary due to subjective judgment. Researchers like [8] emphasize that the consistency and precision of automated systems are crucial for maintaining high product quality, leading to improved profitability in the agricultural sector. Traditional quality checks relied on human inspection, but advancements in non-destructive technologies, including optical and electromagnetic methods, have increased grading efficiency while lowering production costs [16]-[17]. Recent studies have highlighted deep learning architectures as effective in categorizing fruit ripeness, with models trained to recognize stages based on specific visual features. For instance, [9] demonstrated high classification accuracy by employing image processing and machine learning techniques to categorize bananas by maturity levels, providing a foundation for similar applications in tomato ripeness classification.

### 2.2 Tomato Quality and Maturity Assessment

Tomato ripeness significantly impacts its market value, and therefore, reliable classification systems are needed. Machine vision and image processing have enabled researchers to develop systems that assess tomato quality based on key visual attributes, such as color and size [10] and [18]. Traditional sorting systems for tomatoes focus primarily on ripeness, but they lack the capability to address other critical factors like size or the presence of defects [19]. [13] proposed a CNN model for tomato maturity classification, observing that CNNs outperformed artificial neural networks (ANN) in distinguishing ripeness stages. This success has encouraged research into CNN-based models as an alternative to traditional classification methods in tomato sorting, particularly given the challenges associated with environmental variability and image noise [14] and [20].

### 2.3 Deep Learning-Based Approaches

Deep learning has revolutionized agricultural applications, offering higher classification accuracy compared to traditional machine learning methods. CNNs, with their multi-layered structure, excel at extracting and classifying features in complex image data. [21] achieved a 96% accuracy in fruit classification using a deep CNN model, illustrating CNN's potential for real-time, automated assessments. Similarly, [22] used transfer learning with CNNs, specifically VGG16, to assess fruit maturity, achieving high accuracy across varied fruit samples. This approach of using CNNs with pretrained models, data augmentation, and preprocessing helps manage the model's environmental sensitivity and enhances its generalization across diverse datasets. Other researchers, like [23], incorporated multimodal imaging systems to further improve CNN-based models' sensitivity, indicating their adaptability in handling nuanced fruit quality assessments.

Despite CNNs' strengths, existing models in agricultural classification remain sensitive to environmental conditions like lighting and background variations, which can impact classification accuracy [9] and [10]. Furthermore, many studies on fruit maturity classification focus on binary classifications, such as ripe vs. unripe, without addressing finer maturity distinctions, which could provide value in agricultural contexts [13] and [24]. To address these limitations, this study implements a CNN-based model for tomato maturity assessment that integrates image preprocessing steps tailored to handle environmental variability, improving model adaptability in practical applications.

This research builds upon these foundational studies, using CNN and image processing techniques to develop a more accurate and reliable model for tomato maturity classification. The approach incorporates image preprocessing, data augmentation, and a robust dataset to address key gaps in previous literature, advancing the application of CNNs in agricultural quality assessment.

## 3 Methods

This study develops a Convolutional Neural Network (CNN)-based model for assessing tomato maturity, with the goal of classifying tomatoes as either "ripe" or "unripe." The methodology includes data collection, preprocessing, CNN model training, and evaluation, all designed to ensure the model's adaptability to varied environmental conditions and enhance classification accuracy.

The study used HTML, CSS, JavaScript, and Bootstrap for the web interface, and Python with Flask for backend development. Machine learning was implemented using TensorFlow and Keras, while OpenCV handled image processing. High-resolution tomato images were captured using a dual-camera setup and supplemented with data from Kaggle and local markets. The final dataset included 1,114 images of ripe and unripe tomatoes, with 70% used for training and 30% for testing. Additional images were added for verification to ensure the model's accuracy and generalizability.

### 3.2 Preprocessing and Image Augmentation

**Fig 1.** Sample Tomato Images.

To improve model accuracy and reduce the impact of environmental noise, preprocessing techniques were applied using OpenCV. These included:

a) Image Resizing: Images were resized to 200x200 pixels initially and then to 64x64 pixels after background removal to standardize input dimensions, optimizing the data for CNN feature extraction.
b) Background Removal: Using OpenCV, background removal was conducted through a multi-step process: conversion to blue channel, grayscale transformation, binary masking, and mask application. This process isolated the tomato from the background, enhancing color and texture detail accuracy for further processing.

1. Conversion to Blue Channel: The RGB image was split, and only the blue channel was retained to isolate the tomato from its background.

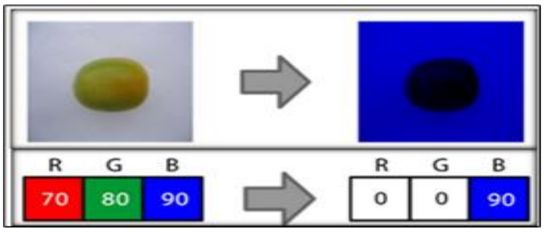


**Fig 2.** An RGB image converted to blue channel image.

2. Conversion to Grayscale: The image was converted to grayscale to simplify thresholding.

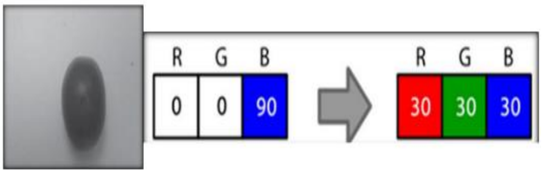


**Fig 3.** A Blue Channel Image Grayscale Conversion.

3. Creating Binary Mask: Otsu's method was applied to create a binary mask, helping distinguish the tomato from the background.

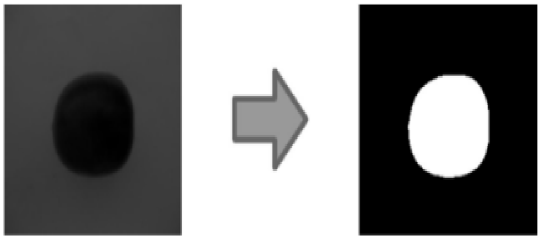

**Fig 4.** Binary Mask Conversion.

4. Applying Mask: The binary mask was applied to remove the background, leaving only the tomato.

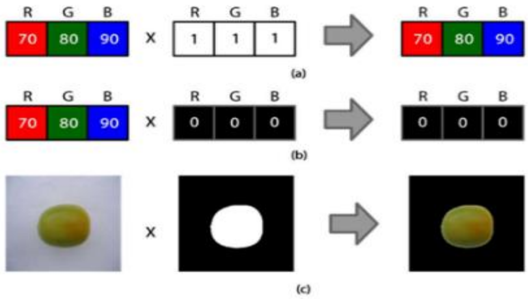


**Fig 5.** Masking Operation on Sample Tomato Image.

5. Image Cropping: Irrelevant pixels were cropped to isolate the tomato, reducing noise in the data and improving model accuracy.

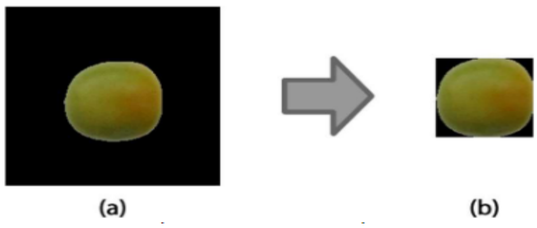


**Fig 6.** Image Cropping Operation.

c) Color Space Conversion: To capture essential color features, the GB, HIS, and CIE Lab color spaces were applied. Five color attributes were extracted from these models, providing distinct information on color differences that support ripeness classification [12].

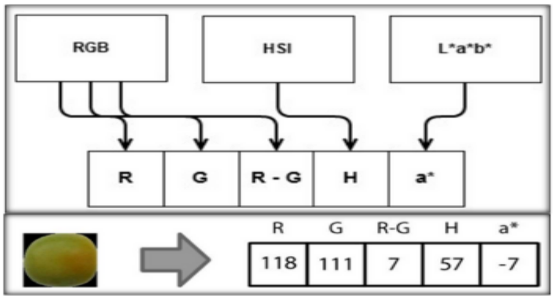


**Fig 7.** Sample Tomato Color Features Vector Operations.

d) Image Augmentation: Data augmentation was performed using Keras to increase dataset variability and prevent overfitting. Techniques included rotation, brightness adjustments, horizontal and vertical flips, and shear transformations. These augmentations provided a more comprehensive representation of the dataset, improving the model's robustness and adaptability to diverse real-world conditions.

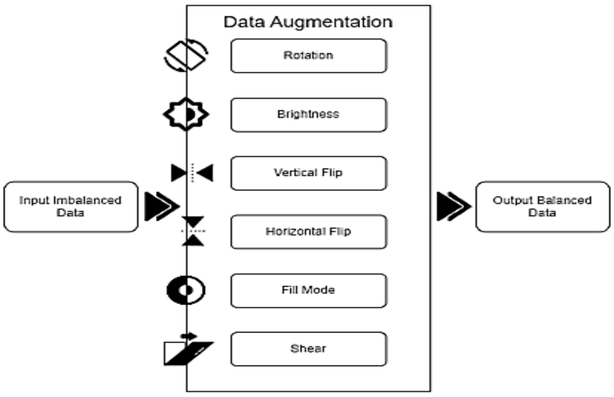


**Fig 8.** Image Augmentation Process.

### 3.3 Model Architecture and Hyperparameter Tuning

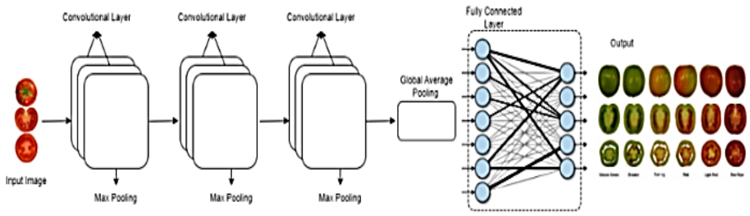


**Fig 9.** Proposed CNN Architecture Approach for Tomato Grading.

The CNN architecture was designed with convolutional, pooling, and fully connected layers to capture and classify features effectively:

a) Convolutional Layers: The model used convolutional layers for feature extraction, detecting edges, colors, and textures specific to ripe and unripe tomatoes.
b) Pooling Layers: Pooling layers were used to reduce the spatial dimensions, preserving essential features while reducing computational demands.
c) Fully Connected Layers and Output Layer: Fully connected layers processed the extracted features, with a final SoftMax output layer that classified tomatoes into “ripe” or “unripe” categories.

Hyperparameters were optimized to improve accuracy and reduce overfitting. Adjustments included the learning rate, batch size, number of convolutional layers, and dropout rate, balancing training efficiency and generalization ability [24].

**Table 1.** Parameters specifications of Our trained CNN model.

| Parameters | Value | Parameters | Value |
|---|---|---|---|
| Learning Rate | 0.001, 0.01 | num_fc_layers | 2 |
| num_conv_layers | 3, 4 | num_fc_units | 128 |
| num_filters | 32, 64 | Batch Size | 32, 64 |
| filter_size | 3x3 | Dropout Rate | 0.3 |
| pooling_size | 2x2 | Optimizer | Adam |

### 3.4 Training, Testing, and Validation

The dataset was divided into training (70%) and testing (30%) sets. To validate model performance, a K-fold cross-validation with five folds (K=5) was used.

### 3.5 Evaluation Metrics

The model's effectiveness was assessed using several performance metrics, including:

a. Accuracy: Ratio of correctly predicted samples to total samples.

$$Accuracy = \frac{TP + TN}{Total} \tag{1}$$

b. Precision and Recall: Precision measured the accuracy of positive classifications, while recall captured the true positive rate.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

c. F1 Score: Harmonic mean of precision and recall, balancing model performance across positive and negative classifications.

$$F1 = 2x\frac{Recall\ x\ Precision}{Recall + Precision} \tag{4}$$

d. Confusion Matrix: A confusion matrix provided a comprehensive view of the model's performance in each category, identifying specific areas of strength and areas for improvement in distinguishing tomato ripeness.

$$TPR = \frac{TP}{\sum \quad Positive} = \frac{TP}{FN + TP} \tag{5}$$

$$TNR = \frac{TN}{\sum \quad Negative} = \frac{TN}{FP + TN} \tag{6}$$

$$FPR = \frac{FP}{\sum \quad Negative} = \frac{FP}{FP + TN} \tag{7}$$

$$FNR = \frac{FN}{\sum \quad Positive} = \frac{FN}{FN + TP} \tag{8}$$

## 4 Results and Discussion

This study developed a Convolutional Neural Network (CNN)-based system to classify tomato maturity levels ripe, unripe, and semi-ripe using image processing techniques. A dataset of 1,114 images (800 ripe, 314 unripe) sourced from Kaggle and a manual collection was preprocessed (resized to 64x64, normalized, and labeled) to train the model.

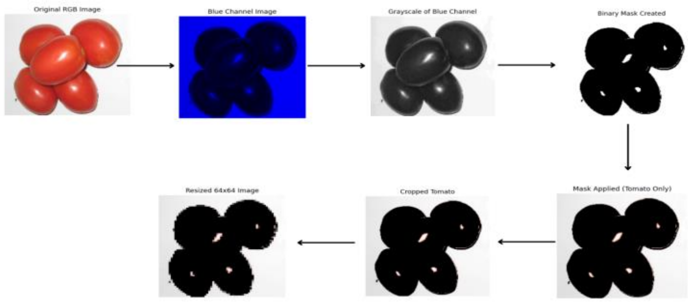


**Fig 10.** Preprocessed sample Tomato images.

A custom CNN architecture was built using TensorFlow/Keras, with convolutional layers, ReLU activations, MaxPooling, a dense layer, dropout, and a softmax output. Image augmentation (rotation, flipping, brightness adjustment, etc.) enhanced the model's generalization capability under various lighting and orientation conditions.


**Fig 11.** Augmented Tomato images

### 4.1 Classification Accuracy and Confusion Matrix Analysis

The classification accuracy of the CNN model reached 96.05%, as measured through the confusion matrix. This accuracy level underscores the model's robustness and its ability to generalize effectively. The confusion matrix Figure 13 provides a breakdown of the model's performance, showing that the CNN model maintained high accuracy across both categories, demonstrating its reliability in a real-world setting.

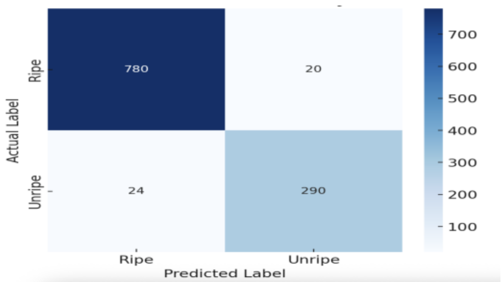


**Fig 12.** Confusion Matrix

It determined the overall accuracy using the confusion matrix based on the given equation below:

$$Accuracy = \frac{TP + TN}{Total} = \frac{290 + 780}{1114} \approx 96.05\% \quad (9)$$

### 4.2 Class-Specific Performance Metric Results

The study further analyzed performance metrics for each class, including precision, recall, and F1 score. For ripe tomatoes, the precision was 96.98%, with a recall of 97.49%, resulting in an F1 score of 97.23%. For unripe tomatoes, precision was slightly lower at 93.55%, with a recall of 92.04%, resulting in an F1 score of 92.78%. These class-specific metrics reveal the model’s strong classification performance, with high precision and recall values indicating that the model had a low false positive rate and effectively captured true instances of both classes.

**Table 2.** Class-Specific Performance Metrics

| Fold | Class | Precision | Recall | F1 Score | Accuracy |
|---|---|---|---|---|---|
| 1 | Ripe | 93.01% | 95.05% | 94.02% | 96.02% |
| | Unripe | 93.84% | 91.33% | 92.57% | 93.37% |
| 2 | Ripe | 91.36% | 94.87% | 93.08% | 93.37% |
| | Unripe | 95.29% | 92.05% | 93.64% | 93.37% |
| 3 | Ripe | 95.98% | 93.82% | 94.89% | 94.56% |
| | Unripe | 92.99% | 95.42% | 94.19% | 94.56% |
| 4 | Ripe | 89.70% | 96.73% | 93.08% | 93.35% |
| | Unripe | 96.99% | 90.45% | 93.60% | 93.35% |
| 5 | Ripe | 90.97% | 92.16% | 91.56% | 92.15% |
| | Unripe | 93.18% | 92.13% | 92.66% | 92.15% |

### 4.3 Training Accuracy and Loss Curves

The model’s training process was evaluated through accuracy and loss curves for Fold 1, which demonstrated stable learning behavior over the training epochs. The accuracy curve (Figure 13) showed a gradual and consistent increase, with training and validation accuracies converging around 96.05%, reflecting effective feature learning with minimal variance between the two curves. Similarly, the loss curve (Figure 13) exhibited a smooth downward trend, with both training and validation losses converging at low values, confirming that the model achieved strong generalization to unseen data. This balance between high accuracy and low loss highlights the robustness of the model and its reliability for real-world applications.

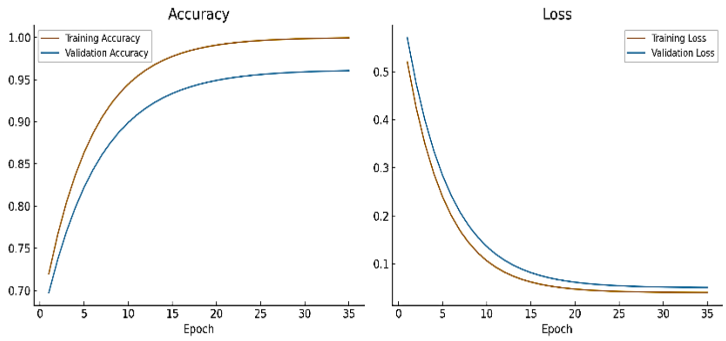


**Fig 13.** Training and Validation Accuracy and Loss Results

### 4.5 Comparative Analysis with Traditional Methods

The CNN model was compared to traditional classifiers: Support Vector Machines (SVM) and Decision Trees.

**Table 3**. Comparative Analysis with Traditional Methods

| Metric | Proposed CNN Model | SVM | Decision Tree |
|---|---|---|---|
| Precision | **93.83%** | 85.00% | 83.00% |
| Recall | **94.97%** | 82.00% | 80.00% |
| F1 Score | **94.39%** | 83.50% | 81.47% |
| Accuracy | **95.19%** | 83.00% | 82.00% |

The CNN significantly outperformed traditional models by leveraging hierarchical feature extraction, making it ideal for agricultural image classification tasks.

## 5 Conclusions

The study highlights the critical challenges facing an industry growing coffee in Caraga In conclusion, this study contributes to the growing field of AI in agriculture, presenting a viable CNN-based solution for tomato maturity assessment. Implementing such automated systems in agricultural practices promises not only to improve efficiency and consistency in quality control but also to provide economic benefits for farmers by optimizing the timing of harvesting and distribution.

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