Classification of Tomato Fruit Ripeness Level Using CNN-SVM Based on Digital Image

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Abstract: Tomato ripeness classification is an important task in post-harvest quality management, as the ripeness level directly influences taste, shelf life, and market value. Conventional ripeness assessment methods based on manual visual inspection are inherently subjective and often yield inconsistent results. To address this limitation, this study proposes an image-based tomato ripeness classification model using a hybrid Convolutional Neural Network–Support Vector Machine (CNN–SVM) approach. In the proposed model, a pretrained ResNet-50 architecture is employed as a fixed feature extractor to derive deep visual representations, while a Support Vector Machine with a Radial Basis Function kernel is utilized for final classification. The model is evaluated using a publicly available tomato image dataset, with the analysis limited to unripe and ripe categories. Image preprocessing procedures include resizing, normalization, and data augmentation, followed by an 80:20 train–test split strategy. Experimental results demonstrate that the proposed CNN–SVM model achieves strong and balanced performance, with an accuracy of 96.56%, a weighted precision of 96.80%, a recall of 96.56%, and an F1-score of 96.57%. These findings indicate that integrating deep feature extraction with an SVM classifier provides an effective and robust solution for tomato ripeness classification, particularly under limited data conditions.

Keywords: Convolutional Neural Network, Support Vector Machine, Tomato Ripeness Classification

1. Introduction

Tomato is an important horticultural commodity widely consumed as both a fresh vegetable and a processed food ingredient, making it a key product in agricultural production and food distribution systems. Tomato quality is strongly influenced by the ripeness level at harvest, as it directly affects taste, shelf life, and market value. Tomatoes are climacteric fruits characterized by high respiration rates and ethylene production during the ripening process. This physiological behavior accelerates post-harvest quality degradation when harvesting is not performed at the optimal maturity stage [1]. Consequently, accurate determination of tomato ripeness becomes a critical factor in post-harvest handling and distribution to maintain product quality and reduce economic losses [2]. Physiologically, tomato ripening is associated with significant changes in skin color caused by chlorophyll degradation and the accumulation of carotenoid pigments, particularly lycopene. These biochemical changes result in a visible color transition from green to red [3]. Several studies have demonstrated that surface color changes are strongly correlated with physiological ripening stages and can thmarkerefore be used as reliable external indicators of tomato maturity [4].

Despite the clear relationship between color changes and ripeness, tomato maturity is still commonly determined through manual visual inspection. This approach is subjective and highly influenced by lighting conditions and human perception, often leading to inconsistent and inaccurate assessment results [5]. Variations in evaluator experience and visual sensitivity may further increase classification errors, especially when distinguishing between closely related ripeness stages. Such inconsistencies can reduce sorting efficiency, increase post-harvest losses, and negatively affect overall quality management in the tomato supply chain. Therefore, computer

vision–based approaches have been proposed as more objective and consistent alternatives for tomato ripeness assessment by analyzing visual features extracted from digital images, enabling automated, repeatable, and reliable classification compared to manual inspection methods [6].

Among computer vision techniques, Convolutional Neural Networks (CNNs) have been widely applied in fruit ripeness classification due to their ability to automatically extract discriminative visual features and achieve high classification accuracy [7]. Several studies have shown that CNNs can effectively distinguish visual characteristics among different tomato ripeness levels, particularly based on surface color changes, achieving high accuracy in image-based tomato ripeness classification tasks [8]. These findings confirm that CNNs represent a promising approach for tomato ripeness classification.

With the advancement of CNN architectures, deeper networks such as ResNet have been increasingly adopted to enhance feature extraction capability [9]. The ResNet-50 architecture is designed with a residual learning mechanism that enables stable training of deep networks without performance degradation [10]. Previous studies have reported that ResNet-50 produces more discriminative and stable visual feature representations for tomato image classification compared to conventional CNN architectures, leading to significant improvements in classification performance [9]. Despite the strong performance of CNNs, most previous studies still employ end-to-end CNN approaches, in which the final classification is performed using fully connected (FC) layers. This approach has limitations when applied to datasets with limited size or high visual variability, such as differences in lighting conditions and background complexity in tomato images. FC layers contain a large number of parameters and tend to learn training-data-specific patterns, thereby increasing the risk of overfitting and reducing the generalization capability of the model on unseen data [9]. Under such conditions, end-to-end CNN models may produce suboptimal decision boundaries for complex feature distributions.

To address this limitation, recent studies have increasingly adopted hybrid approaches that combine CNNs as feature extractors with Support Vector Machine (SVM) classifiers. This strategy aims to leverage the strength of CNNs in extracting high-level visual features while utilizing the strong generalization capability of SVMs, particularly on small- to medium-sized datasets [11]. In addition, SVM with a Radial Basis Function (RBF) kernel has been shown to construct stable non-linear decision boundaries in high-dimensional feature spaces, making it well suited for fruit ripeness classification tasks [12].

Based on these considerations, this study proposes a CNN–SVM–based approach that explicitly addresses the limitations of end-to-end CNN models by employing ResNet-50 solely as a visual feature extractor and using an SVM with an RBF kernel as the final classifier. The proposed method classifies tomato ripeness into two physiological categories, namely unripe and ripe, using a public Tomato Fruits Dataset. This hybrid approach is expected to reduce overfitting and improve model generalization in image-based tomato ripeness classification.

2. Literature Review
Many previous studies on image-based fruit ripeness determination have employed machine learning algorithms to automate the classification process. With the advancement of computer vision, deep learning approaches have become increasingly dominant. In tomato ripeness classification, CNN have been reported to recognize differences in maturity levels more accurately than conventional methods, as they are capable of capturing complex color patterns directly from images [3] [8]. Several studies have also reported that the ResNet-50 architecture is able to produce more stable and discriminative feature representations for fruit images, thereby improving the performance of tomato ripeness classification [13]. Despite the strong performance of CNNs, end-

to-end CNN models that rely on fully connected layers as the final classifier are prone to overfitting, particularly when trained on limited datasets.

Consequently, a number of studies have proposed integrating CNNs as feature extractors with conventional machine learning algorithms as classifiers. SVM is frequently selected due to its ability to separate classes in high-dimensional feature spaces and its strong generalization capability. Study [14] demonstrated that the combination of CNN and SVM improves classification accuracy and stability compared to end-to-end CNN models. Similar findings were also reported by [14], which stated that SVM is more robust in handling CNN-extracted features on small-sized datasets.Tomato ripeness determination has been extensively investigated in previous studies, particularly through color-based approaches. As reported by [15], Numerous studies have explored image-based tomato ripeness classification using color features extracted from RGB, HSV, and CIE Lab color spaces. Study classified tomato ripeness into three classes *unripe*, semi-ripe, and ripe using RGB image features and reported that color information plays a dominant role in distinguishing maturity levels. Furthermore, [16] stated that tomato color is a primary indicator for detecting the ripening process, where color changes from green to red represent different ripeness stages. These findings indicate that visual-based tomato ripeness assessment is closely associated with physiological changes occurring during the ripening process.

In this study, the *reject* class is not used as an indicator of tomato ripeness because it primarily represents fruit quality conditions, such as physical defects, damage, or non-compliance with quality standards, rather than physiological changes directly related to the ripening process. This approach is consistent with [16], which categorized tomatoes into quality classes based on appearance characteristics such as texture, shape, and surface condition to detect damaged or defective fruits. Therefore, tomato ripeness determination in this study is focused on two classes, namely unripe and ripe. To support this classification task, this study employs an integrated CNN–SVM approach, where a ResNet-50–based CNN is used as a color-based visual feature extractor and SVM is applied as the classifier, aiming to produce a tomato ripeness classification model that is more accurate, stable, and conceptually consistent.
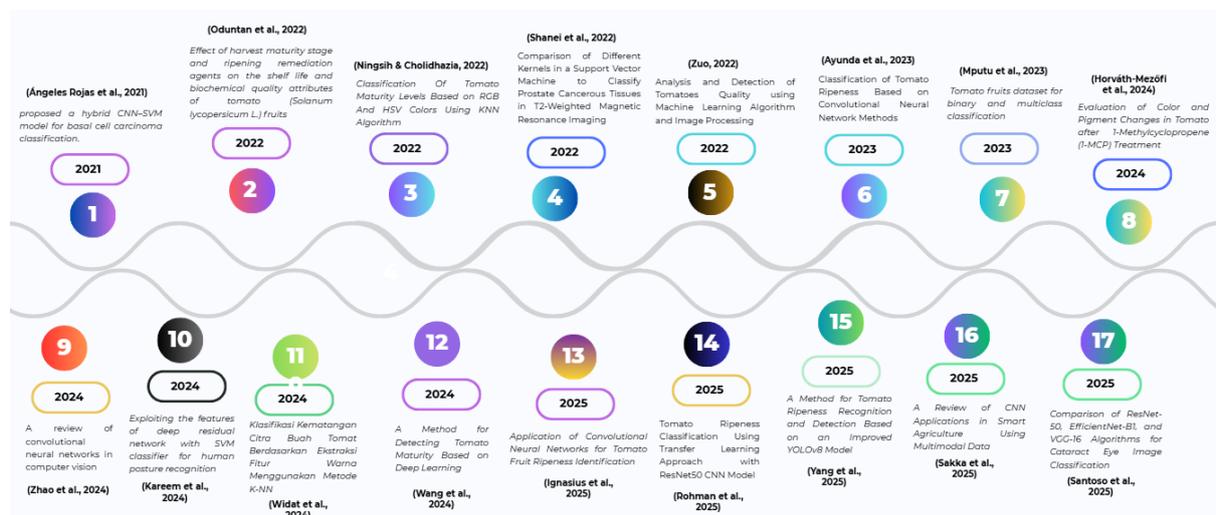

Figure 1. Research Roadmap of Image-Based Tomato Ripeness Classification Studies

Figure 1 illustrates the research roadmap that positions the proposed approach within the progression of previous studies on tomato ripeness classification. Earlier works predominantly relied on end-to-end CNN architectures, which demonstrated strong feature learning capabilities but were prone to overfitting when applied to limited datasets. In contrast, the proposed study is positioned at the intersection of deep feature extraction and classical machine learning, by

employing a pretrained ResNet-50 model solely as a feature extractor and integrating an SVM with an RBF kernel as the classifier. This positioning highlights the technical distinction of the proposed approach, which aims to enhance generalization performance while reducing model complexity compared to end-to-end CNN-based methods.

3.Methods

A. Data Description

The dataset used in this study consists of 2,400 digital images of tomato fruits obtained from the Mendeley Data platform under the title "Tomato Fruits Dataset" [17]. According to the dataset documentation, the images are categorized into three main classes, namely Unripe, Ripe, and Reject, with 800 images per class. The Unripe class represents immature tomatoes, the Ripe class represents fully mature tomatoes, and the Reject class represents tomatoes with quality issues such as defects or damage.
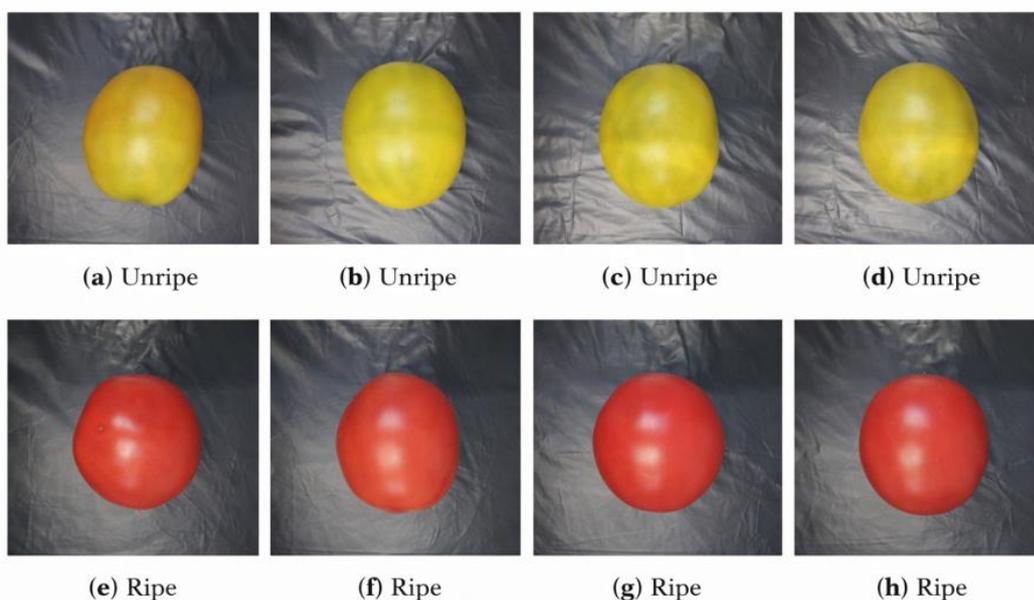

Figure 2. Sample Images of Unripe and Ripe Tomatoes from the Dataset

In this study, only the classes that are directly related to tomato ripeness are utilized. Therefore, the Reject class is excluded, and the dataset is reduced to two ripeness-related categories, namely Unripe and Ripe, resulting in a total of approximately 1,600 images used for training and evaluation. The Unripe category is characterized by tomatoes with green or yellowish coloration that has not fully transitioned to red, while the Ripe category is characterized by tomatoes with a uniformly red surface, indicating full maturity. All images are provided in JPG format and exhibit variations in illumination conditions and background complexity. This visual diversity enhances the robustness of the proposed classification model by exposing it to realistic image variations during training and testing.

B. PreProcessing Data

During the preprocessing stage, tomato images are first resized to 224×224 pixels to match the standard input dimensions required by the ResNet-50 architecture and to ensure data uniformity. Pixel values are then normalized to the range 0–1 to reduce the influence of illumination intensity variations and to stabilize the model training process.To enhance data variability and improve model generalization, image augmentation techniques are applied. These include brightness adjustment to simulate different lighting conditions and contrast adjustment to emphasize variations between bright and dark regions. Such augmentations encourage the model to focus

more effectively on surface color changes of tomatoes, which serve as a primary visual indicator of ripeness. After the preprocessing stage is completed, the dataset is divided using a train–test split strategy, with 80% of the data used for training and 20% for testing. This data partitioning ensures that model evaluation is performed objectively on previously unseen samples, thereby providing a reliable assessment of the model's generalization capability.

C. CNN-SVM for Tomato Ripeness Classification

Tomato images are processed using a hybrid CNN–SVM framework, in which the CNN component is dedicated exclusively to feature extraction, while the final classification is performed by a Support Vector Machine (SVM). In this study, the ResNet-50 architecture is employed as the feature extractor due to its proven effectiveness in learning deep and discriminative visual representations through residual learning mechanisms. ResNet-50 consists of a series of convolutional layers organized into residual bottleneck blocks, each comprising stacked 1×1, 3×3, and 1×1 convolutional layers with identity shortcut connections. These residual connections enable the network to preserve low-level visual information while progressively learning higher-level semantic features, thereby improving training stability and representation quality in deep architectures.

The preprocessed tomato images are forwarded through the ResNet-50 network up to the final convolutional stage, with the original classification layers of the network removed. Consequently, feature extraction is performed after all residual bottleneck blocks have been applied, ensuring that the extracted features encode high-level visual patterns related to tomato ripeness. At this stage, the network produces feature maps with a spatial resolution of 7×7 and a depth of 2048 channels. These feature maps are subsequently aggregated using Global Average Pooling (GAP), which computes the average value of each feature channel across spatial dimensions. The GAP operation transforms the feature maps into a compact 2048-dimensional feature vector for each image, effectively summarizing the dominant visual characteristics while reducing spatial redundancy and mitigating overfitting.

The resulting feature vectors primarily capture surface color distributions and intensity patterns, which are strongly correlated with the physiological ripening process of tomatoes. By replacing fully connected layers with GAP, the model reduces the number of trainable parameters while retaining essential semantic information, leading to more robust and generalizable feature representations. The extracted 2048-dimensional feature vectors are then used as input to an SVM classifier to perform the final classification into two ripeness categories, namely *unripe* and *ripe*. The SVM employs a Radial Basis Function (RBF) kernel, which enables the construction of a non-linear decision boundary in the high-dimensional feature space. This kernel selection is particularly suitable for handling complex feature distributions produced by deep CNNs, where class separation is rarely linear. During training, the CNN remains in a fixed pretrained state without fine-tuning, and the learning process focuses solely on optimizing the SVM hyperparameters to achieve optimal class separation.

By decoupling the processes of feature extraction and classification, the proposed CNN–SVM approach leverages the representational power of deep residual networks alongside the strong generalization capability of SVMs. This hybrid strategy results in a classification framework that is not only accurate and stable but also reproducible, making it well suited for image-based tomato ripeness classification and broader agricultural quality assessment applications.
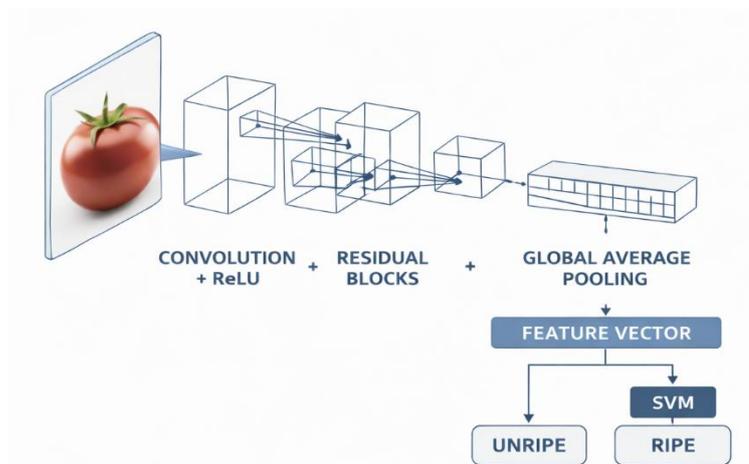
Figure 3. ResNet-50 Feature Extraction and SVM Classification Framework

D. Training Strategy and Model Evaluation

The model is trained using a CNN–SVM approach, where a ResNet-50 network pretrained on ImageNet is employed solely as a feature extractor without additional fine-tuning, while the learning process is focused on the Support Vector Machine (SVM) classifier. Classification is performed using a Radial Basis Function (RBF) kernel due to its effectiveness in handling non-linear class separation in high-dimensional feature spaces. Hyperparameter optimization is conducted using a Grid Search strategy to determine the optimal values of the C parameter (1 and 10) and gamma (γ) (0.001, 0.01, 0.1, and 1).

Table 1. Hyperparameters

	Parameter	Value
1	Feature Dimension	2048
2	C Parameter	{1, 10}
3	Gamma (γ)	{0.001, 0.01, 0.1, 1}
4	Hyperparameter Optimization	GridSearch
5	Input Image Size	$224 \times 224 \times 3$

Model performance is evaluated using accuracy, precision, recall, and F1-score metrics, with particular emphasis on the F1-score to provide a balanced assessment of the two-class classification performance. The evaluation is performed on a test dataset obtained through an 80:20 train–test split, ensuring that the reported results reflect the model's ability to generalize to previously unseen data.
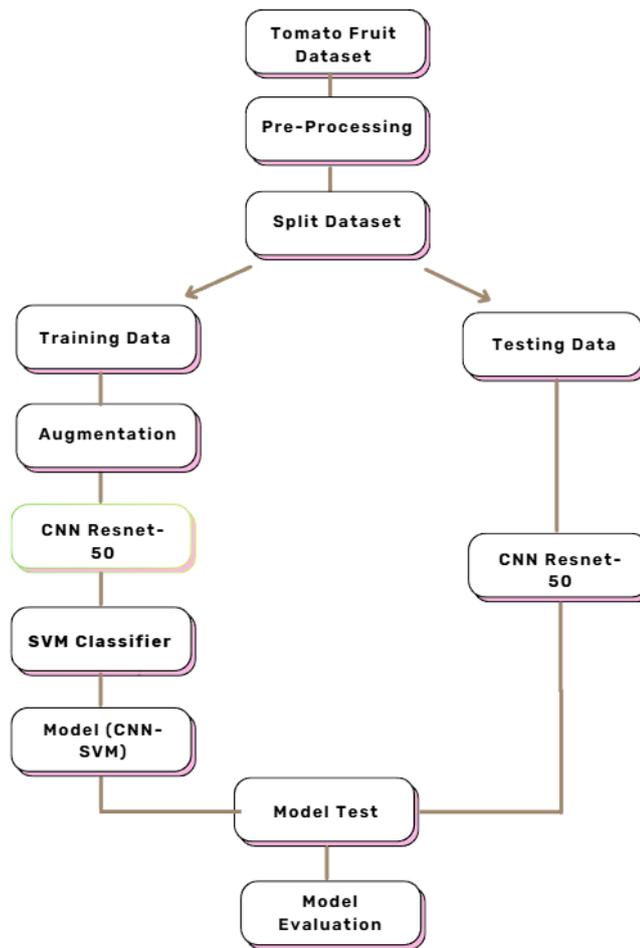
Figure 4. CNN-SVM Model Design

3. Results and Discussion

The proposed CNN–ResNet50 + SVM model was evaluated using a test dataset consisting of 320 tomato images, comprising 148 unripe and 172 ripe samples. Model performance was assessed using accuracy, precision, recall, and F1-score metrics to evaluate the effectiveness of the classification approach. The experimental results demonstrate that the proposed model achieves strong and balanced performance in distinguishing tomato ripeness levels. Quantitative evaluation results show that the model achieved an overall accuracy of 96.56%, with a weighted precision of 96.80%, recall of 96.56%, and F1-score of 96.57%, as summarized in Table 2.

Table 2. Performance of CNN–ResNet50 + SVM Model

	Metric	Value (%)
1	Accuracy	96.56
2	Precision (Weighted)	96.80
3	Recall (Weighted)	96.56
4	F1-Score (Weighted)	96.57

These results indicate that the proposed CNN–SVM framework is capable of producing reliable predictions while maintaining a balanced trade-off between precision and recall, which is essential for practical ripeness assessment applications. A class-wise performance analysis further confirms the robustness of the proposed approach. The unripe class achieved a precision of 93%, recall of 100%, and F1-score of 96%, indicating that all unripe tomato samples were correctly classified without false negatives.

Table 3. Class-wise Classification Performance

	Class	Precision (%)	Recall (%)	F1-Score (%)	Support
1	Unripe	93	100	96	148
2	Ripe	100	94	97	172

This result suggests that the color-based visual features extracted by the ResNet-50 network are highly effective in capturing the distinctive characteristics of immature tomatoes. For the ripe class, the model achieved a precision of 100%, recall of 94%, and F1-score of 97%, demonstrating strong recognition capability with only a limited number of misclassifications. To provide a more comprehensive evaluation context, the performance of the proposed CNN–SVM approach is further analyzed through comparison with an end-to-end CNN-based classification approach. This approach is employed as a comparator because it represents the conventional classification scheme commonly adopted in CNN-based studies, in which feature extraction and classification are jointly performed within a single network. In this evaluation, the ResNet-50 architecture is utilized as an end-to-end CNN model by leveraging ImageNet-pretrained weights and employing a fully connected–softmax layer as the final classifier. All images are processed with an input size of 224 × 224 pixels, and augmentation strategies identical to those used in the CNN–SVM experiments are applied, including brightness adjustment, contrast adjustment, and horizontal flipping, to ensure fair and consistent training conditions. The same dataset as the CNN–SVM approach is used, consisting of unripe and ripe tomato images, with an identical 80:20 train–test split to maintain comparable class distributions and test samples.

Model training is conducted in two stages. The first stage is performed for 10 epochs, during which all ResNet-50 layers are frozen and only the classification layer is trained to stabilize the learning process. The second stage involves fine-tuning for an additional 10 epochs, in which the final layers of ResNet-50 are partially unfrozen to adapt the learned feature representations to the characteristics of tomato images, using a lower learning rate to ensure stable weight updates. Optimization is carried out using the Adam optimizer with sparse categorical cross-entropy as the loss function, and early stopping as well as learning rate reduction on plateau are applied to mitigate overfitting. The evaluation results show that the end-to-end ResNet-50 model achieves an accuracy of 95.94%, with a weighted precision of 96.24%, recall of 95.94%, and an F1-score of 95.93%. These results indicate that the end-to-end CNN approach exhibits strong classification capability in distinguishing tomato ripeness levels from digital images. However, when compared with the proposed CNN–SVM approach, the end-to-end model demonstrates slightly lower performance across all evaluation metrics. This performance difference suggests that employing SVM as the final classifier enhances the model's generalization capability by more effectively exploiting the visual features extracted by ResNet-50, particularly when applied to datasets of limited size. A quantitative comparison of the performance of both approaches is summarized in Table 4.

Table 4. Class-wise Classification Performance

Model	Accuracy(%)	Precision (%)	Recall (%)	F1-Score (%)
CNN End-to-End	95,94	96,24	95,94	95,93
CNN-SVM	96,56	96,80	96,56	96,57

Based on Table 4, the CNN–SVM approach demonstrates superior performance compared to the end-to-end CNN model across all evaluation metrics. The observed improvements in accuracy, recall, and F1-score indicate that decoupling the feature extraction and classification stages by employing SVM leads to a more stable decision boundary. This finding reinforces the argument that using SVM as the final classifier can enhance the model's generalization capability,

particularly when applied to datasets with limited size and high visual variability. Differences in classification error patterns can be further observed through the confusion matrices presented in Figure 5.
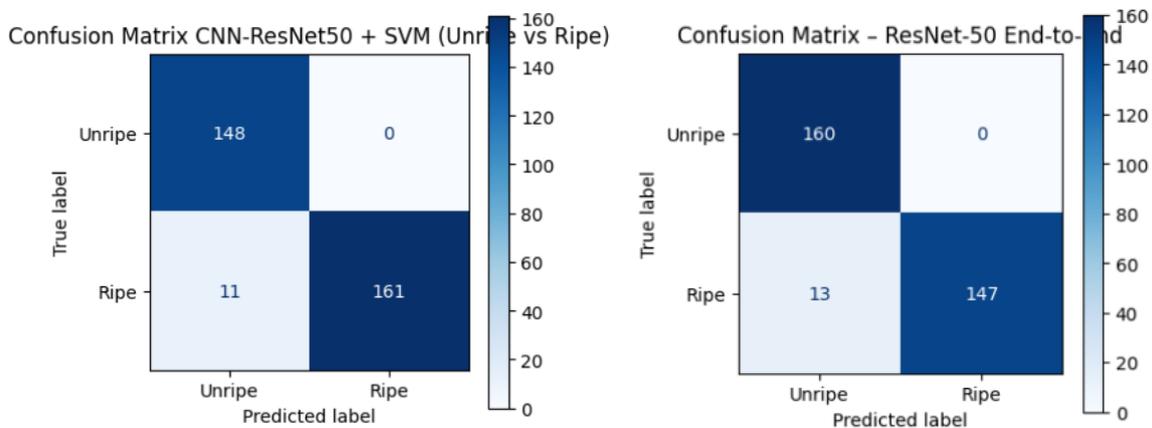

Figure 5. Confusion Matrix CNN-SVM and CNN End

For the CNN–SVM model, all 148 tomato images belonging to the unripe class were correctly classified as unripe, with no misclassification into the ripe class. Regarding the ripe class, out of a total of 172 test images, 161 were correctly classified as ripe, while 11 ripe samples were misclassified as unripe. Consequently, misclassification in the CNN–SVM model occurred only in one direction, namely from the ripe class to the unripe class.

By contrast, the end-to-end ResNet-50 model also correctly classified all 160 unripe images in the test set without errors. However, for the ripe class, 147 out of 160 images were correctly classified as ripe, while 13 ripe samples were misclassified as unripe. Compared with the CNN–SVM approach, the end-to-end model exhibits a higher number of misclassifications in the ripe class. The dominance of diagonal values in both confusion matrices indicates that both models are capable of effectively separating tomato ripeness classes. Nevertheless, the smaller number of misclassifications observed for the CNN–SVM model suggests that this approach provides more stable generalization when distinguishing tomatoes at transitional ripeness stages based on visual surface characteristics.

4. Conclusions

This study proposes a CNN–SVM–based classification model for tomato ripeness assessment using digital images. In the proposed approach, a pretrained ResNet-50 network is utilized as a visual feature extractor without additional fine-tuning, while a Support Vector Machine with a Radial Basis Function kernel is employed as the classifier to distinguish tomatoes into two ripeness categories, namely *unripe* and *ripe*. This strategy is designed to combine the deep visual feature representation capability of CNNs with the strong generalization ability of SVMs. Experimental results demonstrate that the proposed model achieves high classification performance, with an overall accuracy of 96.56%, a weighted precision of 96.80%, recall of 96.56%, and an F1-score of 96.57%. The confusion matrix analysis indicates that all unripe samples are correctly classified, while misclassifications in the ripe class occur only in a limited number of samples. These findings suggest that the visual features extracted by ResNet-50 are highly discriminative and effective in representing tomato ripeness characteristics. Furthermore, comparative evaluation with an end-to-end ResNet-50 model confirms that the proposed CNN–SVM approach consistently provides improved performance and more stable generalization. By clearly separating the feature extraction and classification stages, the proposed model offers an effective and robust alternative to fully end-to-end CNN approaches, particularly when applied to limited-size datasets.

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