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A Review on Tomato Quality Classification Using Transfer Learning and Machine Learning Classifiers

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Abstract
Tomato quality classification plays an important role in modern agriculture, influencing both market value and supply chain efficiency. Manual sorting methods are often unreliable and impractical for large-scale processing. Recent advances in computer vision and artificial intelligence have led to the development of automated classification systems. This review investigates hybrid approaches that combine deep feature extraction using transfer learning models with traditional classifiers such as SVM, decision trees, and instance-based learners. The paper summarizes recent techniques used for tomato ripeness and quality grading, analyzing the datasets, model performance, architectural improvements, and deployment challenges. It further highlights potential directions to enhance scalability, efficiency, and practical implementation in agricultural environments.

Keywords: Tomato quality classification, Transfer learning, Convolutional neural networks, Machine learning classifiers, InceptionV3, Agricultural automation, Feature extraction, Hybrid models

1. Introduction
Tomatoes are among the most widely cultivated and consumed vegetables globally, serving as a vital source of nutrition and income for millions of farmers. The accurate assessment of tomato quality—based on ripeness, size, color, and presence of physical damage—is crucial for both commercial trade and consumer satisfaction. Traditionally, this process relies heavily on manual inspection, which is time-consuming, inconsistent, and impractical for large-scale operations.
With advancements in artificial intelligence and computer vision, automated classification systems have emerged as promising solutions to overcome the limitations of manual sorting. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong capabilities in extracting complex visual features from images. However, these models often require large annotated datasets and significant computational resources to train effectively from scratch.
To address these challenges, **transfer learning** has been adopted as a reliable approach. It leverages pre-trained CNN architectures to extract meaningful features from tomato images, which can then be used in downstream classification tasks. By combining transfer learning with traditional machine learning

classifiers such as Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (KNN), hybrid systems have shown promising results in terms of accuracy, efficiency, and adaptability.

This review presents a comprehensive study of recent research in tomato quality classification using hybrid approaches. The goal is to analyze and compare various models, identify key trends, highlight challenges, and propose directions for future research. A particular focus is given to methods that apply deep feature extraction from CNNs and use classical ML classifiers for the final prediction phase, as these frameworks offer a practical balance between performance and deployability in agricultural applications.

2. Literature Review

The rapid growth of computer vision and artificial intelligence has enabled significant progress in tomato quality and maturity classification. Various approaches using deep learning, transfer learning, and hybrid techniques have been proposed to enhance accuracy, speed, and generalizability. This section presents a comprehensive review of fifteen relevant studies, arranged in chronological order.

1. **De Luna et al. (2019)** compared traditional machine learning and deep learning models for tomato size classification. On a limited dataset, the SVM classifier proved more effective than deep CNNs like VGG16 and InceptionV3, reaching approximately 95% accuracy. This highlighted that conventional models can outperform complex architectures when trained on smaller datasets.
2. **Chinapat et al. (2021)** examined several transfer learning models including ResNet152V2, InceptionResNetV2, and MobileNetV2 for ripeness detection. Among them, ResNet152V2 showed top-tier performance with 99.46% accuracy. However, the experiments focused solely on binary classification tasks and lacked practical testing in uncontrolled environments.
3. **Taspinar (2022)** explored CNN-based tomato species classification using AlexNet, VGG16, and InceptionV3. AlexNet achieved full classification accuracy (100%) on a clean, well-structured dataset. The findings suggest that simpler architectures can outperform deeper ones under specific data conditions.
4. **Begum and Hazarika (2023)** presented PKAMMF, a model combining multiscale detection with attention mechanisms guided by prior domain knowledge for disease detection. Tested on 45,000 tomato images, it attained 91.96% mAP. The work focused exclusively on diseases, limiting its applicability for maturity grading.
5. **Marshal and Jayadi (2023)** implemented a VGG-19 model to classify tomatoes as unripe, ripe, or spoiled. The approach achieved 91.11% accuracy following careful adjustment of model parameters. However, its evaluation was restricted to controlled conditions without field-level validation.
6. **Liu and Wang (2023)** proposed a disease classification model utilizing attention-based feature encoding combined with prior knowledge. Their system achieved 91.96% mAP on a complex and diverse dataset. Despite solid performance, the solution was not adaptable for ripeness detection tasks.
7. **Anonymous (IRJMETS, 2023)** described a hybrid system integrating InceptionV3 for feature extraction with SVM and KNN for classification. The framework attained accuracy between 96% and 97% in grading tomato maturity levels. However, it lacked comparative analysis with state-of-the-art deep learning techniques.
8. **Santhosh and Hemanth (2024)** introduced a modular classification pipeline combining CNN-based feature extractors (MobileNetV2, InceptionV3, ResNet50) with machine learning classifiers.

Evaluated under varying lighting and backgrounds, it consistently scored above 97% accuracy. Still, it did not explore real-time object detection methods.

9. **Waseem et al. (2024)** optimized a ResNet-18 model through pruning and quantization for fast and efficient tomato maturity prediction. Their version attained 97.81% accuracy and near-instant inference times on Jetson Nano devices. Nevertheless, field performance under variable conditions was not validated.
10. **Mousse et al. (2024)** proposed a dual-layer model combining segmentation and RNN with attention for multilingual maturity classification. With training on over 50,000 images, the model reached 97.06% accuracy. However, it has yet to be tested on mobile or embedded platforms.
11. **Hao et al. (2024)** developed GSBF-YOLO, an object detector integrating GhostNet modules, SimAM attention, and BiFPN. The method achieved a mean precision of 89.4% and over 110 FPS in 3-class tomato ripeness detection. While efficient, the dataset size was limited and edge-device trials were absent.
12. **Raut et al. (2025)** proposed a hybrid classification model using InceptionV3 for deep feature learning with multiple classifiers (SVM, RF, KNN). Their system showed strong multi-class grading performance, achieving up to 97.54% accuracy. However, no tests were conducted for real-time or mobile deployment.
13. **Eloge and Zou (2025)** combined ResNet-50 and Vision Transformer (ViT) in a hybrid model to detect four stages of ripeness. Their fusion model yielded 98% accuracy and an F1-score of 0.99. Despite impressive results, the model's computational intensity limits its suitability for edge devices.
14. **Dong et al. (2025)** proposed GPC-YOLO, a YOLOv8n variant enhanced with GSConv and SimAM modules for ripeness classification. It reported 98.7% accuracy and inference speeds up to 201 FPS. While highly efficient, the system focused exclusively on maturity and not broader quality metrics.
15. **Anonymous (arXiv: 2503.10940, 2025)** introduced a pruned and quantized CNN targeting six-stage maturity detection in real time. Tested on Jetson Nano, the system balanced efficiency and accuracy well. Yet, testing on larger datasets and outdoor conditions is still required.

Table 1: Comparative Analysis of Tomato Classification Techniques

S. No	Authors (Year)	Method Used	Dataset & Target Classes	Outcomes	Identified Gaps
1	De Luna et al. (2019)	SVM vs CNNs	Small dataset, tomato sizing	~95% accuracy (SVM best)	Deep CNNs underperformed on limited data
2	Chinapat et al. (2021)	ResNet152V2, InceptionResNetV2	3 maturity stages	~99.46% accuracy	Focused on binary classification only
3	Taspinar (2022)	AlexNet, VGG16, InceptionV3	9 tomato species	100% accuracy (AlexNet)	Static images only, no edge testing
4	Begum & Hazarika	PKAMMF	45K disease	91.96%	Not applicable

	(2023)	(Multiscale + Attention)	images	mAP	for ripeness classification
5	Marshal & Jayadi (2023)	VGG-19 CNN	Unripe, ripe, spoiled	~91.11% accuracy	No real-world or hardware deployment
6	Liu & Wang (2023)	Attention + prior knowledge	10 disease classes	91.96% mAP	Not transferable to ripeness tasks
7	Anonymous (IRJMETS, 2023)	InceptionV3 + SVM/KNN	3-grade tomato grading	96–97% accuracy	Lacks benchmarking and visualization
8	Santhosh & Hemanth (2024)	TL + ML hybrid pipeline	3 ripeness levels	>97% accuracy	No YOLO or real-time comparison
9	Waseem et al. (2024)	Pruned + Quantized ResNet-18	6-class dataset (Jetson)	97.81% accuracy	Field testing not done
10	Mousse et al. (2024)	Segmentation + RNN + Attention	>50K multilingual images	97.06% accuracy	Not tested on edge hardware
11	Hao et al. (2024)	GSBF-YOLO (YOLOv5s + GhostNet)	~440 images (3 stages)	89.4% mAP, 110.9 FPS	Dataset small, lacks deployment
12	Raut et al. (2025)	InceptionV3 + ML classifiers	Binary & multi-class grading	97.54% accuracy	No real-time implementation
13	Eloge & Zou (2025)	ResNet-50 + Vision Transformer	4 ripeness stages	98% accuracy, 0.99 F1	Heavy model, not mobile-friendly
14	Dong et al. (2025)	GPC-YOLO (YOLOv8n + GSConv)	4.3K images, 3 maturity classes	98.7% accuracy, 201 FPS	Maturity only, no hybrid integration
15	Anonymous (arXiv:2503.10940, 2025)	Pruned + Quantized CNN	Real-time, 6 maturity levels	Fast & accurate on Jetson	Lacks field-scale validation

3. Proposed System Architecture

This section outlines the workflow of the proposed tomato quality classification system, which integrates a deep learning-based feature extractor with machine learning classifiers to achieve efficient and accurate grading.

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Figure 1. Workflow of the proposed hybrid model for tomato quality classification.

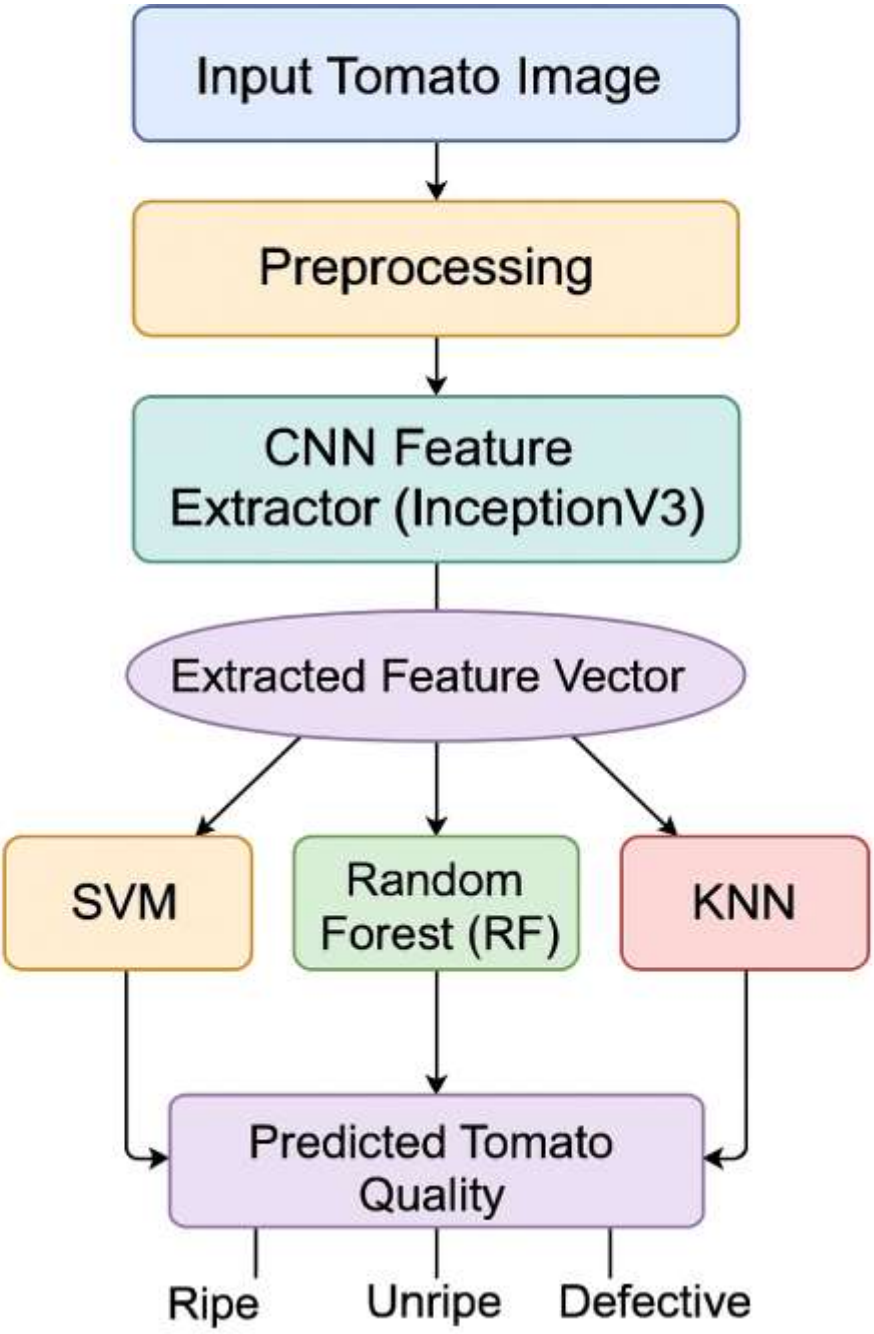

Figure 1: Proposed System Architecture for Tomato Quality Classification

4. Challenges and Limitations

Despite considerable progress in the field of automated tomato quality classification, several challenges and limitations persist that hinder large-scale, real-time, and robust deployment. These issues are observed both in standalone deep learning systems and in hybrid models combining transfer learning wih traditional classifiers.

One of the primary challenges lies in the **availability and diversity of datasets**. Many models are trained on small, well-structured datasets collected under controlled conditions. Such datasets often lack the variability present in real-world farm environments, including fluctuating lighting, occlusion, fruit overlap, and background noise. This limits the generalization ability of trained models when applied to dynamic field conditions.

Another critical limitation is the **computational complexity** of deep learning architectures. Although transfer learning reduces the need for training from scratch, models like InceptionV3, ResNet152V2, and Vision Transformers still require substantial memory and processing power. This restricts their usage in low-resource settings, such as handheld devices or edge-based IoT platforms used by farmers and small-scale producers.

Additionally, while several studies achieve high accuracy in laboratory experiments, **few models are optimized for real-time performance**. Achieving high frame rates, fast inference speed, and low latency on embedded platforms remains a key concern. Methods such as pruning and quantization help address this issue, but often at the cost of reduced accuracy or class-wise imbalance.

The **lack of standardized evaluation protocols** across different works also presents a challenge. Variations in dataset size, number of classes, augmentation techniques, and evaluation metrics make it difficult to perform direct comparisons or benchmark new models fairly.

Moreover, **hybrid systems combining deep feature extraction with machine learning classifiers**, while effective in some cases, can introduce additional complexity in tuning, training, and integration. These models may also suffer from overfitting if not properly regularized, especially when used with limited data.

Lastly, **deployment challenges**, such as integration with automated grading systems, real-time sorting lines, or drone-mounted cameras, are still underexplored. Most of the research remains at the experimental or proof-of-concept level, without field validation or user-level testing.

Addressing these limitations requires collaborative efforts in dataset standardization, hardware-efficient model design, and real-world deployment trials, ensuring that automated tomato classification systems can meet industrial demands.

6. Conclusion and Future Scope

This review has emphasized the significance of automated tomato quality classification in modern agriculture, offering an efficient alternative to traditional manual sorting. Hybrid models that utilize deep feature extraction through transfer learning combined with machine learning classifiers like SVM, Random Forest, and KNN have shown strong potential for accurate and scalable classification.

Despite these advancements, several challenges remain. Most existing models are trained on small or controlled datasets, making real-world generalization difficult. Deployment in low-resource environments, such as on embedded systems or mobile devices, is still limited due to model complexity and size.

Looking ahead, there is great scope for adopting lightweight and optimized architectures such as MobileNet, EfficientNet, and pruned CNNs for real-time applications. Expanding datasets with greater variation in ripeness, lighting, and environmental conditions will further improve model robustness. Future research can also explore ensemble approaches, attention mechanisms, and integration into IoT-based or robotic systems for smarter farming solutions.

By addressing these areas, the development of practical, accurate, and efficient tomato classification systems can move closer to real-world adoption, supporting both small-scale farmers and large-scale agricultural automation efforts.

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