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AI-Powered Tomato Grading: Transfer Learning Optimize

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Abstract: *The increasing demand for high-quality tomatoes and large-scale production has underscored the importance of efficient inline quality grading systems. Manual grading is labor-intensive and costly, which has driven the development of automated solutions. This study introduces a hybrid approach that combines pre-trained convolutional neural networks (CNNs) for feature extraction with traditional machine learning algorithms, such as support vector machines (SVM), random forest (RF), and k-nearest neighbors (KNN), for classification. A tomato image dataset was created using the NVIDIA Jetson TX1, and preprocessing techniques were applied to enhance feature learning. The CNN-SVM model excelled, achieving 97.50% accuracy in binary classification (healthy vs. rejected) and 96.67% accuracy in multiclass classification (ripe, unripe, rejected). When tested on a public dataset, the CNN-SVM model achieved 97.54% accuracy, outperforming other hybrid models. Key performance metrics, including accuracy, recall, precision, specificity, and F1-score, were also evaluated.*

Keywords: Feature extraction, machine learning algorithms, tomato, image preprocessing

I. INTRODUCTION

Tomatoes are among the most common and well-known vegetables in our daily lives and are a vital horticultural crop globally. They hold substantial importance in the food industry, as highlighted by data from FAOSTA. Transfer learning (TL) has gained popularity in addressing complex image classification problems, especially when training data is limited. TL allows the use of pre-trained models, like Convolutional Neural Networks (CNNs), to extract high-level features from images. For tomato quality assessment, transfer learning models such as ResNet, VGG16, and MobileNet can be fine-tuned for specific classification tasks. In 2021, global tomato production reached 189 million tons, emphasizing the need for efficient sorting and grading systems. Traditional manual methods rely on human experts, which are labor-intensive, time-consuming, and subject to subjectivity and error. These limitations can lead to inconsistent quality assessments and delays in the delivery of fresh produce. To address these challenges, automated sorting and grading systems have emerged as a promising solution. Using advanced technologies, these systems can accurately classify tomatoes based on various quality parameters, ensuring consistency, efficiency, and improved product safety.

Agriculture plays a crucial role in economic stability and development, extending beyond food provision to support income generation and rural livelihoods. After extracting features with TL, machine learning (ML) algorithms, such as Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN), can be used for classification. These classifiers are effective for fruit classification, where identifying categories like "ripe," "unripe," and "overripe" is essential. SVM, in particular, has shown strong results due to its capacity for handling high-dimensional data and complex decision boundaries. Advanced analytical techniques, sometimes requiring high-powered microscopes, are essential to identify disease indicators that are only detectable in specific parts of the electromagnetic spectrum, invisible to the naked eye.

Tomato quality is evaluated based on attributes such as color, size, shape, texture, and imperfections like bruises or blemishes, all of which impact market value and consumer acceptance. For instance, color variations indicate ripeness levels, size, and shape irregularities may suggest growth issues, while texture assesses freshness and firmness. Defects, such as bruises, cracks, or spots, usually indicate physical damage or pathogens. Traditionally, trained inspectors

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visually assess these parameters, making the process labor-intensive, subjective, and prone to error. Manual inspections are often inconsistent, especially for large quantities requiring rapid evaluation, leading to the adoption of automated systems that use advanced imaging techniques, machine learning algorithms, and computer vision for more objective and efficient analysis. Automated systems employ high-resolution cameras and sophisticated image processing algorithms to capture and analyze visual tomato features, with hyperspectral imaging techniques revealing chemical compositions and hidden defects beyond standard RGB imaging. These systems operate continuously, offering real-time quality assessments to reduce post-harvest losses and ensure consistent product quality.

Fig 1.Dataset

Machine learning has shown impressive effectiveness in a broad array of applications, such as quality assessment, crop disease detection, handwritten digit recognition, natural language processing, and audio and speech recognition. In the food industry, machine learning is particularly valuable for sorting and grading fruits and vegetables, addressing issues like human error, subjectivity, labor costs, and time-intensive processes. Machine learning-based systems offer improved efficiency, accuracy, and consistency in quality assessment.

While many studies have investigated fruit and vegetable quality assessment, this research makes several unique contributions:

- **Specific Focus on Tomatoes**: This study is tailored to address the unique characteristics and challenges of tomato quality assessment.
- **Real-World Applicability**: The model was developed using a dataset collected under uncontrolled environmental conditions, demonstrating its effectiveness in diverse, real-world scenarios.
- **Hybrid Approach**: This research introduces a novel hybridmodel that combines the strengths of CNNs and traditional machine learning algorithms. CNNs excel at feature extraction with minimal computational resources, while traditional algorithms offer faster training times, achieving a balance between accuracy and efficiency.
- **Dataset**
- **Description**: Details on the dataset used for tomato quality assessment, including the number of images, variety of tomatoes, quality attributes (such as ripeness and defects), and conditions of image acquisition.
- **Data Preprocessing**: Explanation of preprocessing steps applied to the images, like resizing, normalization, and augmentation.

Feature Extraction

- **CNN Features**: Overview of the CNN architecture used for feature extraction, including the number of layers, filters, and activation functions.
- **Traditional Features**: If applicable, a description of traditional features extracted from the images (e.g., color, texture, and shape).

Machine Learning Models

- **CNN Model**: Specifications of the CNN architecture used for classification, including the number of layers, neurons, and activation functions.

- **Traditional Machine Learning Model**: Description of the traditional machine learning algorithms used (e.g., SVM, Random Forest) and their hyperparameters.

Hybrid Model

- **Integration**: Explanation of how CNN features were combined with traditional machine learning algorithms to create the hybrid model.
- **Training**: Details on the training process, including the optimization algorithm, learning rate, and batch size.

Evaluation Metrics

- **Metrics**: Specification of evaluation metrics used to assess model performance, including accuracy, precision, recall, F1-score, and confusion matrix.

Experimental Setup

- **Data Splitting**: Description of how the dataset was divided into training, validation, and testing sets.
- **Hyper parameter Tuning**: Explanation of the process for tuning hyperparameters for both the CNN and traditional machine learning models.

Tomato quality significantly impacts both market value and consumer acceptance. Traditional manual grading, which relies on human expertise, is often time-consuming, subjective, and prone to errors, leading to inconsistencies in quality assessment and slowing the efficient distribution of tomatoes. As a major agricultural commodity in China, tomatoes face challenges related to disease, with China leading the world in both tomato planting area and total output. Tomato diseases, such as bacterial spot, late blight, leaf mold, yellow leaf curl virus, Botrytis cinerea, early blight, bacterial pulp necrosis, gray leaf spot, and sclerotinia, pose significant threats to yield and quality. Traditional expert diagnosis, while valuable, is often constrained by time and the availability of skilled professionals.

II. PURPOSE

To develop a system that can accurately and efficiently grade tomatoes based on their quality using artificialz intelligence (AI). The system utilizes transfer learning to optimize performance, which involves leveraging pre-trained models and adapting them to specific tomato grading tasks. This approach aims to:

Increase Accuracy: Ensure that the grading system reliably differentiates between various grades of tomatoes based on color, size, texture, and other quality indicators.

Improve Efficiency: Automate the tomato grading process to speed up the sorting and packaging, reducing the need for manual labor and human error.

Enhance Scalability: Develop a solution that can be scaled easily for large-scale farming operations or processing plants without needing significant adjustments or retraining.

Reduce Costs: By automating the grading process, the system can help reduce labor costs, while also minimizing waste through better quality control.

Support Sustainability: The AI-powered system can help minimize food waste by ensuring that tomatoes are sorted based on quality, ensuring better use of each batch.

Adapt to Diverse Tomato Varieties: Transfer learning allows the system to adapt to different types of tomatoes or regional variations, making it more versatile for various agricultural markets.

III. OBJECTIVE OF SYSTEM

To develop an AI-powered tomato grading system using transfer learning techniques to optimize classification accuracy, efficiency, and scalability. The system aims to automatically assess tomato quality based on visual characteristics such as color, size, and texture, enabling faster and more consistent grading for agricultural and commercial applications.

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IV. SYSTEM ARCHITECTURE

In the agricultural and food industries, evaluating the quality of tomatoes is a critical task that influences product grading, pricing, and marketability. Traditional quality assessment methods are often manual, subjective, time-consuming, and susceptible to human error. As a result, there is an increasing demand for an automated system capable of swiftly and accurately assessing the quality of tomatoes based on key criteria such as size, color, ripeness, and the presence of defects.

SYSTEM ARCHITECTURE

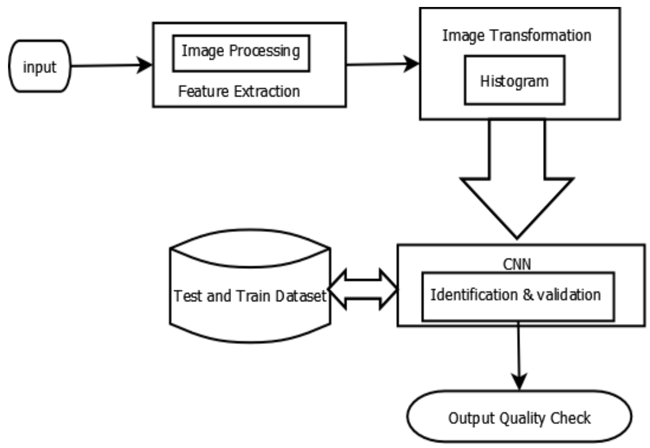

Fig.2 System Architecture

1. Input

This is the starting point where images or data are fed into the system. The input could be raw images that need to be processed and analyzed.

2. Image Processing & Feature Extraction:

- **Image Processing:** This stage likely involves preprocessing the input images to make them suitable for analysis. It could include operations like resizing, noise reduction, or normalization.
- **Feature Extraction:** In this phase, key features from the images are extracted. These features could be edges, textures, or other relevant characteristics that help in distinguishing different aspects of the image.

3. Image Transformation:

- **Histogram:** This part of the process might involve transforming the image data into a form that highlights certain features. A histogram transformation, for example, could be used to enhance contrast or highlight specific intensity values within the image.

4. Test and Train Dataset:

This represents a collection of images that are used to train the CNN model and also to test its performance. The dataset is split into training data (used to train the model) and testing data (used to validate the accuracy and performance of the model).

5. CNN (Convolutional Neural Network):

Identification & Validation: Here, the CNN model is applied to the images to identify and validate the features or objects of interest. CNNs are highly effective for image classification and object recognition tasks due to their ability to learn spatial hierarchies of features.

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6. Output Quality Check:

After processing and analysis by the CNN, the output is subjected to a quality check to ensure that the results meet the required standards. This step could involve verifying the accuracy of the model's predictions or ensuring that the identified features align with expectations.

This workflow is typical in applications like image recognition, computer vision, and automated quality inspection, where it's crucial to accurately identify and analyze features within images. The use of CNNs is common in such tasks because of their strong performance in handling image data.

V. RESULT

1. Image Classification

1	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
2	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
3	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
4	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
5	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
6	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
7	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
8	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
9	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
10	G:/Code 23-24/24 Python Project/TomatoQuality/...	Old
11	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
12	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
13	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
14	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
15	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
16	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
17	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
18	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
19	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
20	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
21	G:/Code 23-24/24 Python Project/TomatoQuality/...	Ripe
22	G:/Code 23-24/24 Python Project/TomatoQuality/...	Unripe
23	G:/Code 23-24/24 Python Project/TomatoQuality/...	Unripe
24	G:/Code 23-24/24 Python Project/TomatoQuality/...	Unripe
25	G:/Code 23-24/24 Python Project/TomatoQuality/...	Unripe
26	G:/Code 23-24/24 Python Project/TomatoQuality/...	Unripe
27	G:/Code 23-24/24 Python Project/TomatoQuality/...	Unripe
28	G:/Code 23-24/24 Python Project/TomatoQuality/...	Unripe
29	G:/Code 23-24/24 Python Project/TomatoQuality/...	Unripe

Fig 3.Input Data

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Fig 4. Image Classification

This image contains a grid of images labeled as "Ripe," "Old," and "Unripe." It shows the results of a tomato classification model, where the AI predicts the ripeness of tomatoes.
Some images appear blurry, indicating possible dataset quality issues.

2. Model Summary

It displays the architecture of a deep learning model.
The model is based on EfficientNetB7, a pre-trained model with 64,097,687 parameters.

Layer (type)	Output Shape	Param #
efficientnetb7 (Functional)	(None, 2560)	64,097,687
batch_normalization (BatchNormalization)	(None, 2560)	10,240
dense (Dense)	(None, 256)	655,616
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 3)	771

Fig 5.Model Summary

The architecture includes batch normalization, dense layers, and dropout layers.
The final output layer has three classes (Ripe, Old, Unripe).

3. Training and Validation Graphs

The left graph shows the training and validation loss over five epochs.The right graph shows the training and validation accuracy over five epochs.
The training accuracy increases initially but then decreases, indicating **overfitting**.
Validation accuracy remains constant, suggesting the model is not generalizing well

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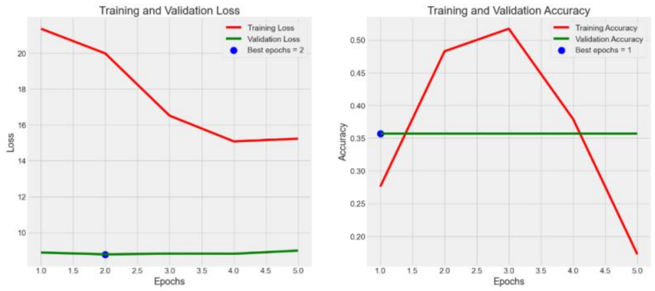


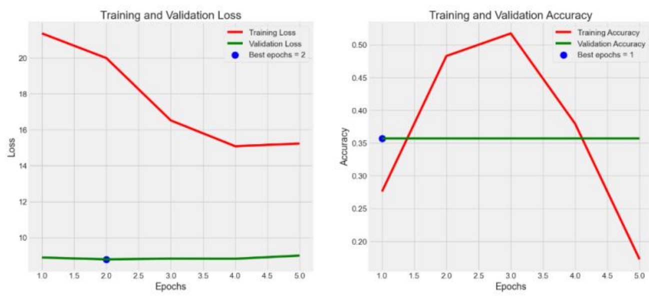
Fig 6.Model Graph

4. Model Performance

Shows the final train, validation, and test accuracy and loss values.

The training accuracy is 0.31, validation accuracy is 0.35, and test accuracy is 0.26.

These low values indicate poor model performance, possibly due to insufficient data, overfitting, or improper hyperparameter tuning.



5. Dataset Performance

A list of file paths where the dataset is stored. The dataset contains images categorized into three classes: Old, Ripe, and Unripe. Ensuring a balanced dataset is crucial for improving model performance.

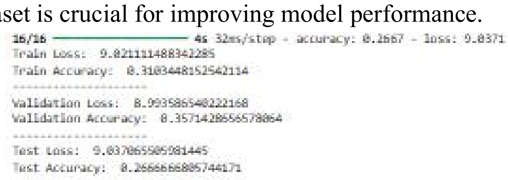


Fig 7.Result Summary

VI. CONCLUSION

We proposed a new approach for grading tomato quality based on external image features. This method combines pre-trained neural networks for feature extraction with traditional machine learning algorithms for classification, creating a hybrid model. Fine-tuning techniques were applied to the pre-trained networks, allowing the deep layers to effectively learn and focus on the complex and important features of tomato images. Additionally, various image preprocessing techniques were implemented to enhance feature extraction and improve overall performance. The features extracted from these networks were then classified using Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) classifiers. Our experiments clearly demonstrated the effectiveness of the fine-tuned networks, with Inceptionv3 achieving the highest accuracy. As a result, Inceptionv3 was selected for further feature extraction and used in our classification models.

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