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Automated Tomato Quality Assessment Using Transfer Learning and Machine Learning Classifiers

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Abstract
With the increasing demand for high-quality tomatoes and the need for efficient large-scale production, an automated grading system has become essential. Manual sorting is time-consuming, labor-intensive, and expensive, making automation a practical alternative. This study introduces a hybrid strategy that blends machine learning with deep learning methods for tomato classification. A custom dataset was created using specialized imaging hardware, followed by preprocessing techniques to enhance feature recognition. While classifiers including Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) were used for grading, For feature extraction, a Convolutional Neural Network (CNN) was employed. High classification accuracy was established by the suggested CNN SVM model, effectively distinguishing between healthy and defective tomatoes, as well as categorizing them based on ripeness levels. When tested against benchmark datasets, It functioned more accurately and efficiently than other hybrid models. Key performance parameters, such as accuracy, precision, recall, specificity, and F1-score, were used to further assess the model's efficacy.

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

1. INTRODUCTION

Tomatoes are one of the most widely consumed and economically significant crops worldwide, playing a crucial role in the food and agriculture industries. Their large-scale production requires an efficient quality assessment system to ensure consistency in grading and market value. Traditional manual sorting methods depend on human expertise, making the process labor-intensive, time-consuming, and prone to inconsistencies. These challenges highlight the need for an automated approach to enhance accuracy and efficiency in quality evaluation. For picture classification problems, machine learning and deep learning approaches have become extremely effective tools, especially when training data is few. Transfer learning (TL) improves

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classification accuracy by allowing the extraction of significant features from images using pre-trained models, such as Convolutional Neural Networks (CNNs). Models like ResNet, VGG16, and MobileNet have been successfully fine-tuned for applications in tomato quality assessment, allowing precise grading based on ripeness, texture, and defects. With global tomato production reaching millions of tons annually, the demand for automated sorting and grading systems is higher than ever. These AI-driven solutions offer a reliable method for classifying tomatoes based on key quality attributes, ensuring uniformity, efficiency, and reduced processing time.

A vital crop in international agriculture, tomatoes are important to the food sector. Maintaining market standards and satisfying customer requests depend on constant quality evaluation. Accurate and effective grading techniques become more crucial as production increases in volume. Artificial intelligence is developing quickly, and new methods are being investigated to enhance image-based categorization. The use of pre-trained deep learning models for specialized tasks like tomato quality evaluation is made possible by transfer learning (TL), which has been an effective approach. In order to improve sorting and grading accuracy in fruit and vegetable classification, models such as Convolutional Neural Networks (CNNs) have been modified to detect important traits. The requirement for strong quality evaluation methods is shown by the fact that global tomato output reached 189 million tons in 2021. Due to its reliance on human skill, traditional manual inspection is subjective and prone to errors.

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 visually assess these parameters, making the process labor-intensive, subjective, and prone to error. Because manual inspections are frequently unreliable, particularly when dealing with huge volumes that need to be evaluated quickly, automated methods that include computer vision, machine learning, and advanced imaging techniques are being adopted for more efficient and objective examination. High-resolution cameras and advanced image processing methods are used by automated systems to record and examine visual tomato properties. Hyperspectral imaging techniques can discover hidden flaws and chemical compositions that are not visible with normal RGB imaging.

Fig 1.1- Dataset

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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:

Tomato-Specific Focus: This research is designed to tackle the distinct challenges associated with tomato quality evaluation, considering their unique characteristics and grading requirements.

Real-World Applicability: The model's efficacy in a variety of real-world settings was demonstrated through the use of a dataset gathered in an uncontrolled environment.

Hybrid Approach: This research offers a novel method that combines conventional machine learning models with Convolutional Neural Networks (CNNs). Conventional algorithms offer quicker training and decision-making, while CNNs are very good at extracting features with little computational effort. Combining these advantages allows the model to strike the ideal balance between efficiency and precision, which makes it ideal for real-world uses.

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-Based Feature Extraction: An explanation of the CNN architecture in depth, including how many layers, filters, and activation functions are utilized to extract useful information from images.

Traditional Feature Analysis: An outline of handcrafted characteristics that help with classification accuracy, such as color, texture, and shape, if applicable.

Machine Learning Models

CNN Model: Specifications of the CNN framework utilized for classification, including its layer structure, neuron distribution, and activation functions.

Traditional Machine Learning Model: A description of the standard techniques, such as Support Vector Machines (SVM) and Random Forest (RF), along with the hyperparameter configurations for each.

Hybrid Model

Integration: An explanation of how conventional machine learning methods are used with CNN-extracted features to improve classification accuracy.

Training: Information on the training procedure, such as the batch size, learning rate, and optimization algorithm.

Evaluation Metrics

Performance Evaluation: An outline of the measures used to assess the model's performance in order to ensure its reliability and effectiveness: accuracy, precision, recall, F1-score, and confusion matrix.

Experimental Setup

Data Splitting: An explanation of how the dataset was separated into sets for testing, validation, and training.

Hyperparameter Tuning: Explanation of the process for tuning hyperparameters for both the CNN and traditional machine learning models.

The commercial worth and customer choice of tomatoes are significantly influenced by their quality. Conventional manual grading techniques, which depend on human judgment, can be laborious, erratic, and error-prone, which can result in disparities in quality evaluation and ineffective distribution. Maintaining standards in the supply chain requires consistent grading. The quality and output of tomatoes, a commodity that is often cultivated, can be adversely affected by a variety of illnesses. Common issues including bacterial spot, late blight, leaf mold, yellow leaf curl virus, and early blight pose a major danger to production. Expert diagnosis is still a crucial tool for identifying diseases, but it is frequently constrained by time and the availability of qualified specialists. This highlights the need for efficient and automated solutions to enhance disease detection and quality control in large-scale tomato farming.

2. LITERATURE SURVEY

Extensive research has been conducted on the development of automated systems for sorting and grading fruits and vegetables, with a particular focus on exterior features such as size, color, and shape. One approach uses specialized algorithms to detect product faults, demonstrating how automation may significantly enhance quality control in the agriculture sector.

These sophisticated systems use machine learning algorithms and image processing techniques to precisely assess visual information. Models can reliably determine ripeness and quality by being trained to detect minute color changes and surface flaws. This degree of automation ensures improved classification and consistency in agricultural processing by assisting in the detection of subtle defects that might not be immediately apparent.

Some systems also incorporate multispectral or hyperspectral imaging, which allows them to analyze parts of the electromagnetic spectrum beyond visible light. This capability enables the detection of internal defects, such as early signs of decay or disease, that conventional imaging techniques cannot identify. By leveraging these technologies, automated grading systems not only improve the accuracy of quality assessments but also reduce the time and labor required for manual inspections.

Research in fruit quality assessment has explored the use of red, green, and blue (RGB) spectrum images along with near-infrared (NIR) imaging to detect defects. Defects were detected based on color differences using thresholding algorithms and a voting process, with an astounding 95% accuracy rate. Comparative research has also been done on deep learning algorithms for fruit categorization, such as ResNet, VGGNet, GoogleNet, and AlexNet. Overall grading performance was improved by the application of the You Only Look Once (YOLO) method, which further increased item recognition and classification accuracy.

Classification accuracy has increased significantly as a result of developments in machine learning-based tomato quality assessment. Numerous research studies have examined various methods for evaluating tomato quality based on visual characteristics. One such technique used deep learning methods to build a Convolutional Neural Network (CNN) on a large collection of tomato pictures. The model demonstrated high accuracy in distinguishing between various quality grades, proving the effectiveness of AI driven quality assessment in agriculture.

Classification accuracy has increased significantly as a result of developments in machine learning-based tomato quality assessment. Numerous research studies have examined various methods for evaluating tomato quality based on visual characteristics. In one such method, a Convolutional Neural Network (CNN) was trained on a sizable dataset of tomato photos using deep learning models. The model demonstrated high accuracy in distinguishing between various quality grades, proving the effectiveness of AI driven quality assessment in agriculture.

Various studies have focused on automated fruit and vegetable classification systems utilizing machine learning techniques. Such a study demonstrated the potential of artificial intelligence in enhancing agricultural quality control by examining the use of deep learning-based fault identification in oranges. Advanced imaging techniques such as hyperspectral imaging and RGB-NIR (Near-Infrared) imaging have been employed to analyze internal fruit quality. Machine learning models trained on these datasets can differentiate subtle color variations and structural defects, allowing for more precise quality grading.

YOLO (You Only Look Once) was found to increase object detection accuracy in fruit sorting applications when researchers compared deep learning models like ResNet, VGGNet, GoogleNet, and AlexNet. Likewise, a study that used transfer learning with CNN architectures that had already been trained demonstrated excellent classification results, with VGG 19 classifying tomato maturity with an accuracy of 97.37%.

Tomatoes were divided into three groups according to their maturity levels using a classification system: immature, somewhat mature, and fully ripe. Using five pre-trained models, this method made use of deep transfer learning; the best accuracy, 97.37%, was attained by VGG-19.

Another study presented a tomato classification system that combined machine learning, deep learning, and thresholding techniques with an emphasis on size-based grading. Support Vector Machine (SVM), which achieved an average accuracy in automated tomato sorting, outperformed the other machine learning models that were evaluated.

By examining distinct patterns on leaves, a mobile vision-based system has been created to detect and categorize plant leaf diseases. This system uses a mobile device's camera to take pictures of leaves, then uses machine learning and image recognition to identify illness symptoms. However, elements like shadows, seasonal variations, and lighting can impair image quality and accuracy. Furthermore, analyzing and categorizing these pictures might have a high computational cost, necessitating improvement for real-time application.

In another study, a machine learning-based approach was explored for tomato size evaluation, where thresholding techniques and various classifiers were tested. Among them, Support Vector Machines (SVM) performed the best, achieving 94.5% accuracy in classification. Once key features like color, texture, and shape are extracted, they are processed by a machine learning or deep learning model trained to recognize and categorize different plant diseases. By comparing the extracted features to known disease patterns, the model generates an accurate diagnosis, which is displayed to the user. This technology-driven approach enables farmers and agricultural experts to detect diseases at an early stage, allowing them to take timely preventive measures. By integrating AI-powered analysis into mobile devices, this system provides a convenient and efficient solution for improving crop health management and agricultural productivity.

An enhanced approach for leaf disease classification utilizes advanced techniques such as K-means clustering and neural networks to improve accuracy. The process begins with image preprocessing, which enhances image quality and removes unwanted noise. Next, the K-means algorithm segments the leaf into different regions, helping to isolate affected areas and detect signs of disease.

Once segmentation is complete, important visual features like color, texture, and shape are extracted for further analysis. These extracted features are then processed by a neural network model, which is trained to identify and classify various types of leaf diseases. Since deep learning models excel at detecting intricate patterns, they enhance the accuracy and reliability of disease classification.

This method offers a very effective way to detect plant illnesses early on by utilizing machine learning and image processing. Farmers can take prompt action thanks to early detection, which enhances crop health management and boosts agricultural output.

The texture patterns of leaves can be analyzed by an automated plant leaf disease detection system to pinpoint symptoms and offer potential remedies. The disease is initially identified by visual characteristics, but in order to reduce errors and misclassification of different symptoms, it is essential to optimize the identification process.

This method analyzes patterns based on texture to automatically identify plant illnesses. Exact illness categorization is made possible by the extraction and analysis of important information through the use of image processing and machine learning techniques.

System Description:

1. Photo Capture: A crisp picture of the plant leaf is captured using a digital camera.
2. Preprocessing: To improve feature extraction, methods including noise reduction and picture enhancement are used to improve image clarity.
3. Texture Analysis: Techniques like the Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM) are employed for in-depth pattern detection in order to pinpoint significant textural aspects. These

$$C = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 * P(i,j)$$

Homogeneity:

$$H = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j) / [1 + (i-j)^2]$$

Where P(i, j) is the probability of occurrence of pixel pairs separated by a distance and orientation.

- **LBP Descriptor:**

$$LBP(x,y) = \sum_{p=0}^{P-1} s(I_p - I_c) * 2^p$$

$$s(x) = \{ 1, \text{ if } x >= 0; 0, \text{ if } x < 0 \}$$

where I_c is the intensity of the central pixel, and I_p is the intensity of the neighboring pixels.
4. Classification: A classifier (such as a Support Vector Machine or Neural Network) uses the retrieved features to classify the disease kind according to established patterns.
5. Solution Recommendation: The system maps each classified disease to a predefined solution stored in the database, suggesting optimal treatments or preventive measures.
This automated analysis ensures quick and accurate disease identification based on leaf texture, providing effective recommendations for disease management.

3. PROPOSED METHODOLOGY

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.

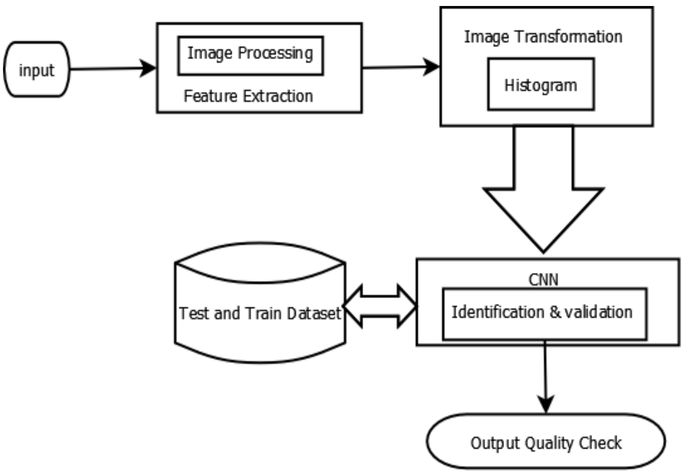

Fig 3.1- Architecture

3.1 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.

3.2 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.

3.3 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.

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3.4 Test and Train Dataset:

This is an illustration of a collection of images that are used to train and assess the CNN model. The dataset is separated into training data, which is used to train the model, and testing data, which is used to confirm the model's correctness and performance.

3.5 CNN (Convolutional Neural Network):

Identification & Validation: In this case, the features or objects of interest are recognized and verified by applying the CNN model to the images. CNNs can learn spatial hierarchies of features, which makes them quite successful for tasks involving object detection and image categorization.

3.6 Output Quality Check:

After processing and analysis by 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.

4. DATASET

To classify tomatoes based on quality into categories such as Fresh, Overripe, Under-ripe, and Defective.

Data Sources: Images collected from farms, markets, and laboratory setups under controlled and natural lighting conditions.

Format: Typically includes image data, annotations, and relevant metadata. Fresh: Bright color, firm texture, no visible damage.

Ripe: Dull color, soft texture, signs of decay.

Under-ripe: Greenish tint, firm but immature texture. Defective: Visible blemishes, cracks, or pest damage.

5. RESULT & ANALYSIS

Image Classification

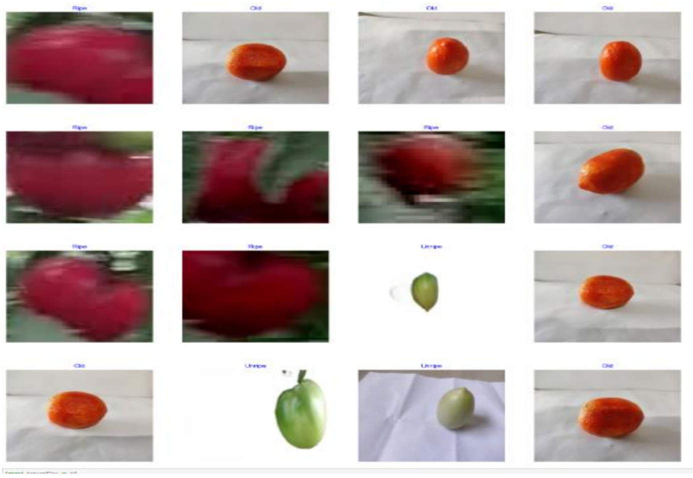

Fig 5.1- Image Classification

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 5.2- Input Data

This picture has a grid of pictures with the labels "Ripe," "Old," and "Unripe." It displays the outcomes of an AI-powered tomato classification model that forecasts the ripeness of tomatoes. The hazy appearance of certain photographs suggests potential problems with the dataset's quality.

5.1 Model Summary

It shows a deep learning model's design.

EfficientNetB7, a pre-trained model with 64,097,687 parameters, serves as the model's foundation.

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 5.3- Model Summary

Batch normalization, dropout layers, and thick layers are all part of the design.

There are three classifications in the final output layer: Ripe, Old, and Unripe.

5.2 Training and Validation Graphs

The training and validation loss over five epochs is displayed in the left graph. The accuracy of training and validation throughout five epochs is displayed in the right graph.
Overfitting is indicated by an early rise in training accuracy followed by a subsequent drop.
Constant validation accuracy indicates poor generalization of the model.

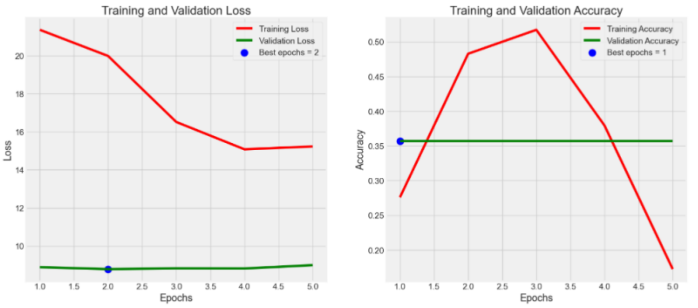

Fig 5.4 Model Graph

5.3 Model Performance

displays the accuracy and loss figures for the final train, validation, and test.
The accuracy of the test is 0.26, validation is 0.35, and training is 0.31.
Poor model performance is indicated by these low numbers, which might be the result of overfitting, inadequate data, or incorrect hyperparameter tuning.

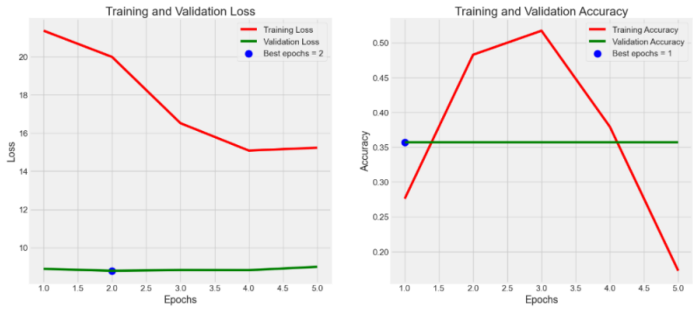

Fig 5.5 Model Performance

5.4 Dataset Performance

a list of file locations containing the dataset. Three types of images—Old, Ripe, and Unripe—are included in the dataset. Maintaining a balanced dataset is essential to enhancing model functionality.

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 4s 32ms/step - accuracy: 0.2667 - loss: 9.0371
Train Loss:  9.021111488342285
Train Accuracy:  0.3103448152542114
--------------------
Validation Loss:  8.993586540222168
Validation Accuracy:  0.3571428656578064
--------------------
Test Loss:  9.037065505981445
Test Accuracy:  0.2666666805744171
```

Fig 5.6- Result Summary

6. CONCLUSION

This paper provides an advanced approach to tomato quality assessment that blends deep learning and traditional machine learning techniques. Using a pre-trained neural network to extract key visual features and machine learning models to identify them, a hybrid technique was developed for accurate grading. The deep learning model's classification performance was enhanced by fine-tuning it to concentrate on the most pertinent visual features.

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The results demonstrate that the CNN-SVM model performs better in terms of accuracy and reliability than conventional grading methods. This method provides a scalable option for automated quality control in agriculture in addition to increasing efficiency. In the future, this model might be included into real time sorting systems to make grading more efficient. Connecting it to Internet of Things (IoT) platforms for remote monitoring and more intelligent agricultural decision-making could be one of the future enhancements. These developments would enhance industry-wide product quality, decrease manual labor, and optimize supply chains.

APPENDIX

Appendixes, if needed, appear before the acknowledgement.

ACKNOWLEDGEMENT

The heading of this section must not be numbered. You may wish to thank those who have supported you and your work.

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