

Fruit Quality Assessment and Freshness Prediction System Using Deep Learning

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Abstract: Fruit quality assessment plays a crucial role in ensuring food safety, reducing post-harvest losses, and maintaining supply chain efficiency. Traditional methods rely on manual inspection or basic image processing techniques, which are often subjective, time-consuming, and inaccurate under varying environmental conditions. This paper proposes a fruit quality assessment and freshness score prediction system using deep learning techniques. The system combines image classification and segmentation approaches to evaluate fruit conditions. It first verifies whether the input image contains an apple, and if not, returns an “object not found” response. For valid apple inputs, the system identifies defective regions such as rot and cracks and computes a quantitative freshness score based on the proportion of defective areas relative to the total fruit surface. Experimental results demonstrate high accuracy and improved reliability compared to traditional methods. The proposed system provides a scalable and effective solution for apple quality evaluation.

Keywords: Deep Learning, Fruit Quality Assessment, Freshness Score, U-Net; Mobile NetV, Image Classification, Semantic Segmentation Computer Vision.

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I. INTRODUCTION

The agricultural and food industries face major challenges in maintaining the quality and freshness of perishable products such as fruits. A significant portion of global food production is lost due to improper quality assessment and inefficient sorting mechanisms. Ensuring accurate and reliable evaluation of fruit quality is essential for reducing waste, improving profitability, and ensuring consumer safety.

Traditionally, fruit quality inspection has been performed manually by human experts. However, this approach is subjective, inconsistent, labor-intensive, and prone to human error due to fatigue and varying judgment standards. In addition, traditional image analysis methods that depend on manually designed features often struggle to handle variations in lighting, surface texture, and natural defects, leading to less reliable results. With the advancement of modern data-driven approaches, new methods have been developed for fruit inspection. These approaches can analyze visual features of fruits and provide more consistent results compared to manual inspection. However, many existing methods only provide simple classification outputs (such as fresh or rotten) and fail to measure the extent of damage, which is important for accurate freshness evaluation. To address these limitations, this research proposes a fruit quality assessment and freshness score prediction system. The

system first verifies whether the given input image contains an apple. If the input does not belong to the expected category, the system returns an “object not found” response. For valid inputs, the system identifies defective regions such as rot and cracks and calculates the proportion of damaged areas. Based on this analysis, the system generates a numerical freshness score, providing a more objective and interpretable evaluation compared to traditional methods. The proposed approach focuses specifically on apple quality assessment and aims to improve consistency, accuracy, and usability in practical applications. By adopting this approach, the work contributes to improving fruit inspection processes and reducing post-harvest losses, supporting better quality control in the agricultural sector.

II. RELATED WORKS

Recent research in fruit quality assessment has focused on improving accuracy and efficiency using image-based analysis techniques. Earlier approaches mainly relied on manual inspection, where experts visually evaluate fruits based on color, texture, and visible defects. However, such methods are subjective, time-consuming, and prone to inconsistency. Some studies have explored traditional image analysis methods using features such as color, shape, and texture to classify fruits into different quality categories. These approaches perform well under controlled conditions but often fail in real-world environments due to variations in

lighting, background, and natural surface irregularities.

Further research introduced learning-based approaches for fruit classification, where images are used to categorize fruits as fresh or defective. While these methods improved classification accuracy, they are limited in providing detailed information about the extent of damage, which is essential for accurate quality assessment. Other works have focused on detecting defects using region-based methods. These techniques identify the int location of defects but are not effective in capturing irregular shapes of spoiled areas, leading to less precise estimation of damaged regions.

More recent studies emphasize pixel-level analysis for identifying defective regions in fruits. This approach enables more accurate measurement of the affected area, which helps in estimating freshness more reliably. From the literature, it is observed that most existing systems either focus on classification or defect detection, but very few combine both verification and detailed defect analysis. Therefore, this work aims to develop a system that first verifies the presence of the required fruit and then evaluates its quality by identifying defective regions and calculating a freshness score.

III. MATERIALS AND METHODS

The system architecture of the proposed fruit quality assessment and freshness score prediction system is presented in Fig. 1. The system is designed to evaluate the quality of apples by integrating image classification and segmentation techniques in a structured workflow. The architecture consists of multiple interconnected components that handle input acquisition, preprocessing, object verification, defect detection, and freshness score generation. Each component plays a significant role in ensuring accurate analysis and reliable output. The system begins with the user interaction layer, where the user uploads an image through a web-based interface. This interface acts as the primary communication medium between the user and the system, allowing easy input submission and result visualization. The interface is designed to be simple and user-friendly so that users can conveniently analyze fruit quality without requiring technical knowledge. Once the image is uploaded, it is passed to the preprocessing stage.

In the preprocessing stage, the input image is prepared for further analysis. This includes resizing the image to a fixed dimension, normalizing pixel values, and applying data

augmentation techniques during training such as rotation, flipping, and scaling. These steps help the system handle variations in lighting conditions, orientation, and background noise. Preprocessing ensures that the input data is consistent and improves the generalization capability of the models. After preprocessing, the system performs object identification to determine whether the input image contains an apple. This step is important to avoid incorrect analysis of unrelated objects. If the input image does not belong to the expected category, the system returns an “object not found” message and stops further processing. This validation step improves the efficiency and reliability of the system. If the image is identified as an apple, the system proceeds to the next stage. The next stage involves defect detection, where the system analyzes the apple surface to identify damaged regions such as rot, bruises, and cracks. This is achieved through pixel-level analysis, which allows precise identification of defective areas. The system separates the damaged regions from healthy portions, providing a clear understanding of the fruit’s condition. This detailed analysis is essential for accurate quality assessment.

Following defect detection, the system evaluates the proportion of defective regions relative to the total surface area of the apple. Based on this evaluation, a numerical freshness score is generated. This score represents the overall quality of the fruit, where higher values indicate better freshness and lower values indicate higher levels of spoilage. The scoring mechanism provides a simple and interpretable way to assess fruit quality.

The entire system is implemented using Python, with TensorFlow/Keras for model development and training. The models are trained on datasets containing images of both healthy and defective apples under different conditions. During training, appropriate loss functions and optimization techniques are used to improve accuracy. The system is validated using test datasets to ensure consistent and reliable performance.

The final output of the system includes the identification result, segmented image highlighting defective regions, and the calculated freshness score. They are displayed through the user interface, enabling users to easily interpret the results. The proposed system provides a consistent and efficient solution for apple quality assessment and demonstrates improved performance compared to traditional manual inspection methods.

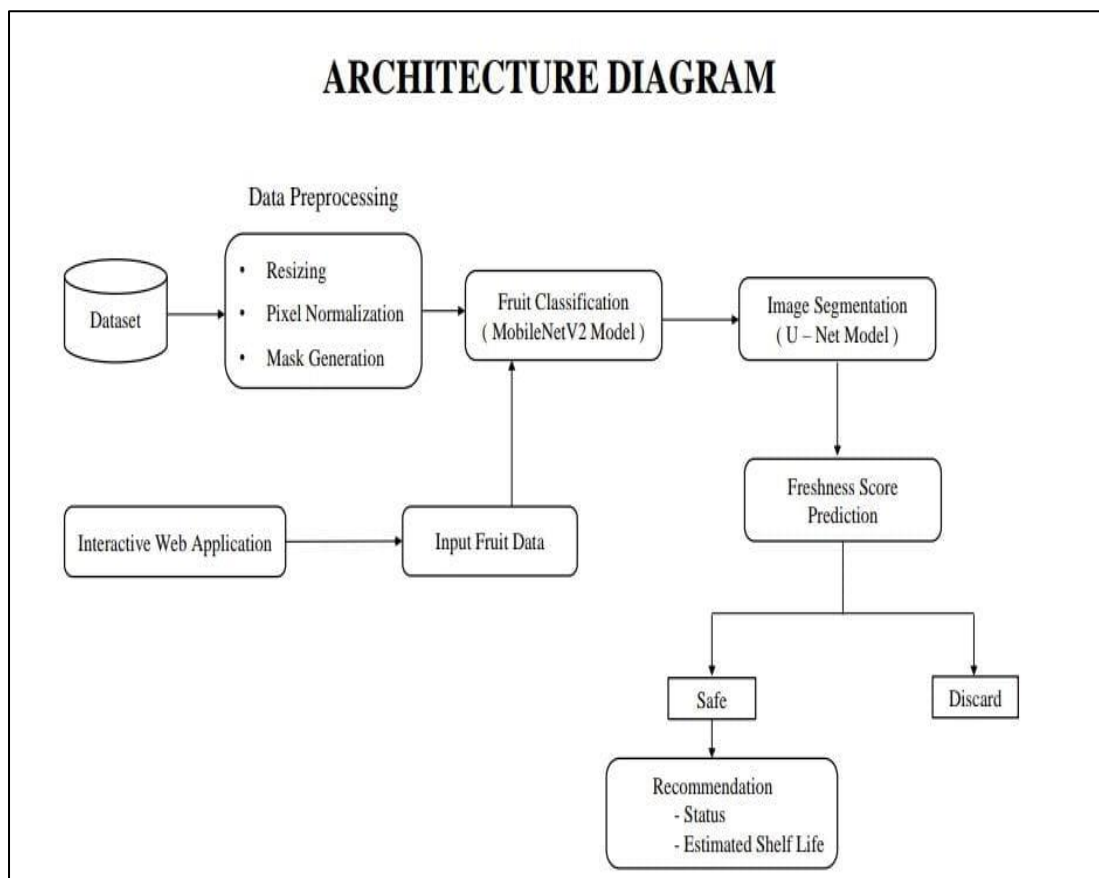


Fig 1 System Architecture for Proposed System

➤ *Input and Preprocessing Module*

The input module allows users to upload images of fruits through a user interface. Once the image is received, preprocessing is performed to standardize the input for further analysis. The preprocessing steps include resizing the image to a fixed dimension, normalizing pixel values, and applying augmentation techniques such as rotation, flipping, and scaling during training. These steps improve the robustness of the system and help it handle variations in lighting conditions, orientation, and background. As a result, the system becomes more reliable when applied to real-world data.

➤ *Apple Identification Module*

In this module, the system verifies whether the input image contains an apple using MobileNetV2 with transfer learning. The model uses pre-trained weights for feature extraction and is fine-tuned for the specific task of apple detection. This approach reduces training time and improves classification accuracy. If the input image is identified as an apple, the system proceeds to the next stage. Otherwise, it returns an “object not found” message and terminates further processing. This ensures that only relevant images are analyzed, improving overall system efficiency.

➤ *Defect Segmentation Module*

For valid apple images, defect segmentation is performed using a U-Net Convolutional Neural Network. This module performs pixel-level analysis to identify different regions of the apple, such as healthy areas, spoiled

regions, and cracks. The architecture consists of an encoder that extracts important features from the image and a decoder that reconstructs the segmented output with precise localization. Skip connections are used to retain spatial information, which helps in accurately detecting irregularly shaped defects. This detailed segmentation enables a more precise evaluation of fruit quality.

➤ *Freshness Score Computation*

After identifying defective regions, the system calculates the proportion of damaged area relative to the total surface of the apple. Based on this analysis, a numerical freshness score is generated. A higher score indicates that the apple is fresh, while a lower score indicates a higher level of spoilage. This scoring method provides a clear and interpretable representation of fruit quality and helps users easily understand the condition of the fruit.

The freshness score is calculated as

$$\text{Freshness Score (\%)} = (1 - (\text{Defective Area} / \text{Total Area})) \times 100$$

Where

Defective Area = pixels classified as damaged

Total Area = total pixels of the apple.

Based on this analysis, a numerical freshness score is generated. A higher score indicates that the apple is fresh, while a lower score indicates a higher level of spoilage. This

scoring method provides a clear and interpretable representation of fruit quality and helps users easily understand the condition of the fruit.

➤ Implementation

The proposed fruit quality assessment and freshness score prediction system was implemented using standard hardware and commonly used software tools to ensure efficiency and practicality. The system was developed on a computer with moderate specifications, showing that it can function effectively without requiring high-end computational resources. This makes the system suitable for use in environments such as academic projects, small-scale setups, and basic testing scenarios.

The system was developed using Python as the primary programming language due to its simplicity and strong support for image processing and deep learning applications. The development process involved writing and executing scripts for data preprocessing, model training, and result generation. For remote access and system monitoring purposes, UltraViewer was used, allowing access to the system from different locations when needed.

The core implementation of the learning models was carried out using TensorFlow/Keras, which provides efficient tools for building and training deep learning models. The apple identification stage was implemented using MobileNetV2 with transfer learning. The model utilizes pre-trained weights to extract important features from images and was further trained to distinguish between apple and non-apple inputs. This approach reduces training time while maintaining good performance.

For defect detection, a U-Net-based architecture was implemented to perform pixel-level segmentation. The model was trained on annotated datasets where defective regions such as rot, cracks, and damaged portions were clearly labeled. During training, suitable loss functions and optimization methods were applied to improve segmentation performance. The model is capable of separating healthy and defective regions, even when the defects are irregular in

shape. The dataset used for training includes images of apples collected under different conditions, such as varying lighting, backgrounds, and orientations. Preprocessing techniques including resizing, normalization, and data augmentation were applied to improve model robustness and generalization.

The dataset was divided into training and testing sets to evaluate system performance. After training, both models were integrated into a single pipeline to ensure smooth execution. When a user provides an image, it is first processed by the classification model to verify whether it is an apple. If the input is valid, the image is then passed to the segmentation model for defect detection. The output of this stage is analyzed to estimate the proportion of damaged regions, which is used to generate a freshness score. The system workflow ensures proper interaction between all components. The input is processed step by step, and the final output is generated in a structured format. The output includes the identification result, segmented image highlighting defective regions, and the calculated freshness score. These results are presented in a simple interface, allowing users to easily understand the condition of the fruit.

Overall, the implementation demonstrates that the system is reliable and efficient, and capable of performing fruit quality assessment using moderate resources. The use of remote access tools like UltraViewer further supports usability by enabling monitoring and control from different locations. The system provides a practical solution for apple quality evaluation and can be extended in future work.

IV. RESULTS AND DISCUSSION

The proposed fruit quality assessment and freshness score prediction system was developed and evaluated to analyze its effectiveness in identifying apples, detecting defects, and estimating freshness levels. The system demonstrated its ability to process input images, verify the presence of apples, and provide meaningful output based on the condition of the fruit.

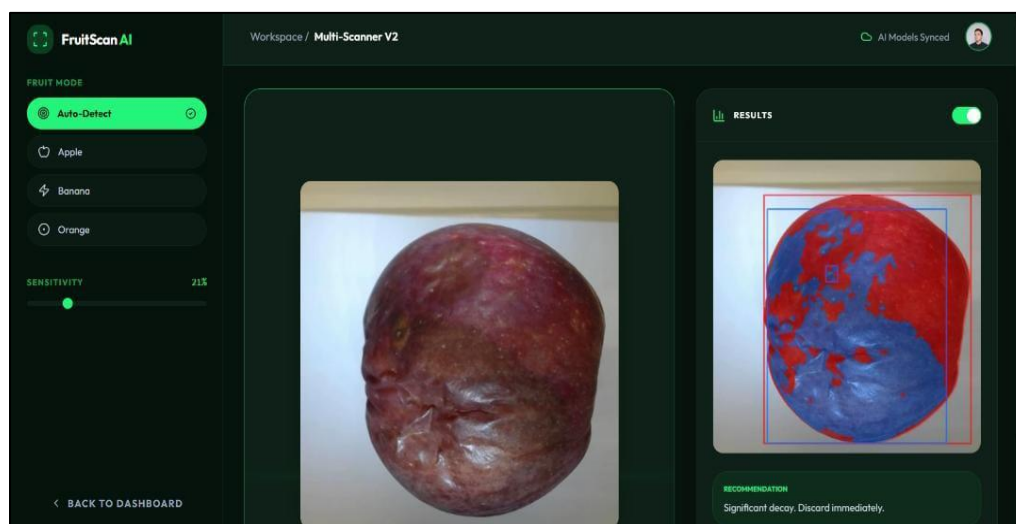


Fig 2 Input Image and Segmented Output

During testing, the system successfully identified apple images and performed defect segmentation to highlight damaged regions such as spoiled areas and cracks. The segmented output clearly distinguished between healthy and defective regions, allowing better visualization of fruit condition. The system was able to detect irregular defect patterns and separate them from healthy portions effectively. A sample representation of the input image and its corresponding segmented output is shown in Fig 2.

To evaluate the performance of freshness estimation, different apple samples were analyzed based on the proportion of defective regions. It was observed that apples with very minimal defects produced higher freshness scores. For instance, a sample with a total area of 58,400 pixels and a spoiled area of 120 pixels (0.2%), with no crack regions,

showed a freshness score close to 99.2%, indicating a fresh apple. In another case, a sample with a total area of 62,150 pixels, spoiled area of 4,200 pixels (6.7%), and crack area of 550 pixels (0.8%) resulted in a freshness score of around 72.0%, which was classified as early-stage spoilage. On the other hand, a sample with a total area of 49,000 pixels, spoiled area of 25,600 pixels (52.2%), and crack area of 2,000 pixels (4.0%) resulted in a very low freshness score close to 0%, indicating severe spoilage.

These observations show that the system effectively relates the extent of damaged regions to the overall freshness of the fruit. As the defective area increases, the freshness score decreases accordingly, providing a clear and interpretable evaluation of fruit quality.

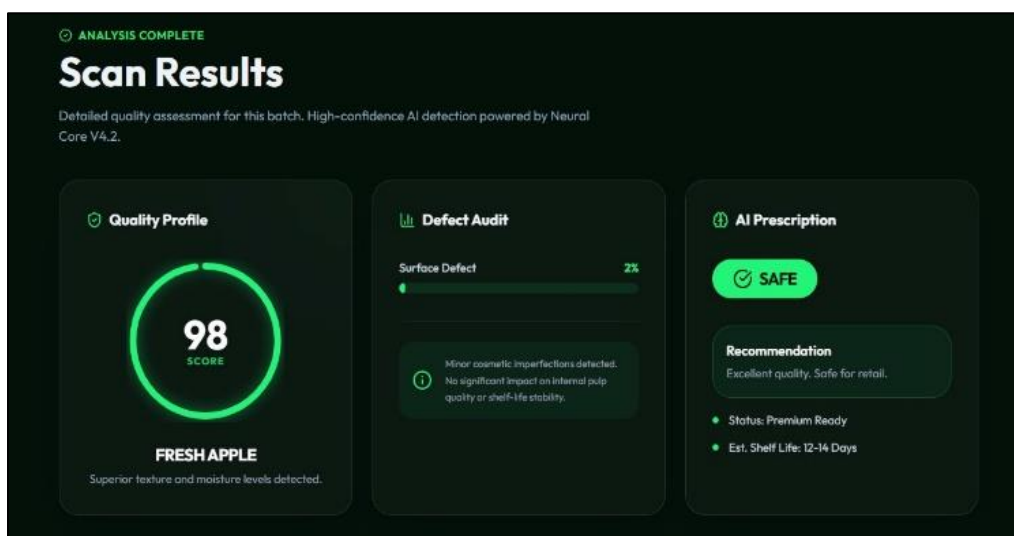


Fig 3 Freshness Score Output and Result Display

V. CONCLUSION AND FUTURE WORK

The proposed fruit quality assessment and freshness score prediction system provides an effective method for evaluating apple quality based on visual analysis. The system verifies whether the input image contains an apple, identifies defective regions such as spoiled areas and cracks, and generates a freshness score based on the proportion of damage. This approach offers a clear and objective way to assess fruit quality compared to manual inspection. The combination of classification and segmentation enables both object verification and detailed defect analysis. The results show that the system can differentiate between fresh and spoiled apples based on the extent of defects. Overall, the system provides a reliable solution for apple quality evaluation. In future work, the system can be extended to support multiple fruit types by using a larger and more diverse dataset. The performance can be improved by including more variations in lighting conditions and defect types. Additionally, the system can be developed into a mobile or web-based application for easier access. Further improvements can focus on faster processing and better defect detection.

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