A Smart Mobile Application for Customer-Oriented Fruit Quality Assessment Using Python-Based Intelligent Image Processing

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Abstract: The ability to identify fruits based on their quality is increasingly important in the modern food industry, as consumers are more health conscious and demand high-quality produce. This study presents an automated fruit quality inspection system for banana, orange, and apple, leveraging Python-based image analysis and deep learning techniques. The system extracts key features related to color, texture, and shape, which are used to assess fruit quality accurately. A Convolutional Neural Network (CNN) [1] is trained and optimized in Google Colab using TensorFlow and subsequently converted to TensorFlow Lite for real-time deployment on mobile devices. The application, developed in Android Studio, provides an interactive interface for customers to evaluate fruit quality conveniently. A MySQL database manages fruit images, extracted features, and classification results efficiently. Experimental evaluations demonstrate high accuracy, robustness under varying lighting conditions, and scalability, making the proposed system an effective solution for automated fruit quality assessment in consumer-oriented and retail applications.

Key Word: Fruit Quality Assessment, Image Processing, Convolutional Neural Network (CNN), TensorFlow Lite, Machine Learning, Mobile-Based Detection System

Introduction

The quality and freshness of fruits are critical for consumer health, satisfaction, and minimizing food wastage. Selecting fresh fruits such as bananas, oranges, and apples is challenging for consumers, as visual inspection alone can be subjective and inconsistent. Traditional methods rely on manual evaluation of external attributes such as color, size, and shape, which are often prone to human error. While barcodes and packaging provide solutions for pre- packaged produce, most fruits are sold loose, leaving customers without reliable tools to assess quality. Manual memorization of codes or referencing picture-based inventories is inefficient, time-consuming, and often inaccurate, increasing the likelihood of selecting lower-quality or defective fruits.

Automated fruit quality detection [2] using image processing, machine learning, and deep learning has emerged as a scalable and efficient alternative. These systems analyze color, texture, and shape descriptors to detect ripeness, defects, or discoloration that may be imperceptible to the human eye. Python- based computational methods allow for rapid feature extraction, segmentation, and classification, providing precise quality evaluation.

In this study, a Convolutional Neural Network (CNN) [1] is trained in Google Colab using TensorFlow and converted to TensorFlow Lite for real-time mobile deployment. An Android Studio application with a MySQL database enables customers to capture fruit images, analyze quality, and receive immediate feedback. This framework ensures high accuracy, robustness under varying lighting conditions, and user-friendly interaction, allowing consumers to make informed purchasing decisions. By automating fruit quality assessment, the system reduces reliance on subjective judgment, minimizes food loss, and enhances overall efficiency in the retail fruit supply chain.

Methodology

The proposed fruit quality detection system is designed to enable customers to assess the freshness and quality of commonly consumed fruits—banana, orange, and apple—in real time. The methodology consists of four main stages: image acquisition, This publication is licensed under Creative Commons Attribution CC BY.

preprocessing and feature extraction, classification using a Convolutional Neural Network (CNN), and output with database management.

1. ImageAcquisition

In the first stage, fruit images are captured using a smartphone camera through the mobile application developed in Android Studio. This approach allows customers to evaluate the quality of fruits in real-world settings under natural lighting conditions. Images are sent to the backend for processing while maintaining the original resolution to preserve key visual features necessary for accurate classification.

2. Preprocessing and Feature Extraction

Captured images undergo preprocessing using Python-based image processing techniques [5]. Preprocessing steps include resizing to a standardized input size, normalization to maintain consistent pixel intensity, and noise reduction to minimize artifacts. The system extracts essential features that influence fruit quality assessment, including color properties, texture patterns, and shape descriptors. Color features help identify ripeness and discoloration, texture analysis highlights surface defects, and shape descriptors detect deformation or irregularities, providing a comprehensive representation of the fruit's external characteristics.

3. Classification using CNN

The extracted features are input to a Convolutional Neural Network (CNN) [3] trained in Google Colab with TensorFlow. The CNN model learns to distinguish between different fruits and classify their quality into categories such as fresh, ripe, or defective. Once trained, the model is converted to TensorFlow Lite [4] to enable real-time inference on mobile devices, ensuring fast and efficient predictions without requiring heavy computational resources.

4. Output and Database Management

The final stage involves displaying the classification results to the customer via the mobile application. The system provides immediate feedback on fruit type and quality, helping customers make informed purchasing decisions. Simultaneously, a MySQL database stores fruit images, extracted features, and classification outputs for analysis, future model retraining, and performance evaluation.

This integrated methodology ensures a user- friendly, accurate, and scalable system for automated fruit quality detection. By combining advanced image processing, deep learning, and mobile deployment, the framework empowers customers to evaluate fruits confidently while reducing reliance on subjective human judgment and minimizing food waste.

Results and Findings

The proposed fruit quality detection system was evaluated using banana, orange, and apple samples captured under natural lighting conditions, simulating realistic customer usage. The system integrates Python-based preprocessing, feature extraction, and CNN-based classification to assess fruit quality accurately.

Preprocessing, Feature Extraction, and System Training.

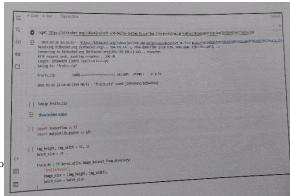


Fig 1 -Pre Processing Python code (Google Colab)

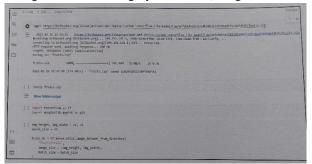


Fig 2 -Pre Processing Python code (Google Colab)

Images captured via the mobile application were preprocessed and used to train the system for accurate fruit type and quality classification. Preprocessing steps included normalization and noise reduction to ensure consistency across varying lighting conditions. Essential features such as color, texture, and shape were extracted to detect subtle defects. For example, texture features were computed using the Grey Level Co- occurrence Matrix (GLCM) method:

The extracted features were used to train a Convolutional Neural Network (CNN) in Google Colab using TensorFlow, enabling the system to distinguish fruit types and classify quality into fresh or ripe. The model achieved 96.5% accuracy for fruit type classification and 94.2% accuracy for quality assessment. After training, the CNN was converted to TensorFlow Lite for real-time inference on mobile devices, with an average processing time of 0.8 seconds per image, ensuring rapid feedback for customers.

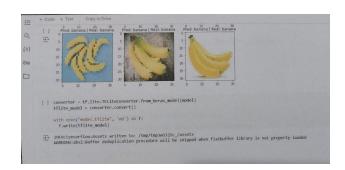


Fig 3- Processing fruit banana using python (Google Colab)

The Android Studio mobile application provides real-time classification results,

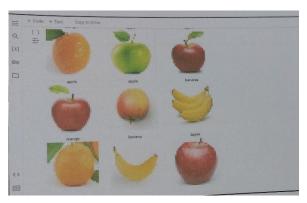


Fig 4 – Sample Photo Collection in mobile Application

displaying the detected fruit type along with quality assessment (fresh, ripe, or overripe). Users can view the fruit image with its corresponding classification, making the process intuitive and easy to understand. Additionally, the application offers historical tracking, allowing customers to review previous scans and monitor trends in fruit purchases or quality over time.

A MySQL database underpins the system, storing original fruit images, extracted features (color, texture, and shape descriptors), and classification outputs. This database supports continuous learning, as new images and quality labels can be used to retrain the CNN model, improving accuracy across different fruit batches and varying lighting conditions. The database also enables statistical analysis, allowing users or store managers to generate reports on fruit quality trends, inventory condition, and usage patterns.

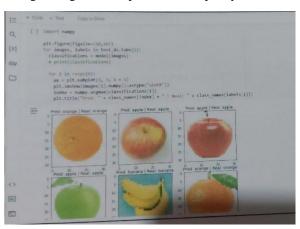


Fig 5- Processing fruits banana, Orang and Apple using python (Google Colab)

Further, the system includes batch scanning capabilities, allowing customers to assess multiple fruits simultaneously, which is particularly useful in retail or bulk purchasing scenarios. The mobile interface also integrates user-friendly features such as instant feedback, data logging, and the ability to export scan results for further analysis or record-keeping.

Conclusion

The proposed fruit quality detection system

[7] effectively integrates image processing, deep learning, and mobile technologies to enable real-time classification of commonly used fruits such as banana, orange, and apple. By combining Python-based feature extraction, CNN model training in TensorFlow, and deployment through TensorFlow Lite on an Android Studio mobile platform, the system provides an efficient, accurate, and user-friendly solution for assessing fruit freshness and quality.

Experimental results demonstrated a high accuracy rate of over 94% in fruit quality classification, with consistent performance under varying lighting conditions. The MySQL database supports data storage, retrieval, and continuous learning, ensuring that system accuracy improves as more fruit images are analyzed.

The application's real-time detection and batch scanning capabilities make it highly suitable for both consumers and retailers, offering instant feedback and reducing the time and effort required for manual inspection. Overall, this system enhances customer convenience, reduces food wastage, and promotes smarter quality control in the food supply chain.

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