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AI-Powered Android Application for Fruit and Vegetable Quality Detection

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Abstract

The proposed project introduces a mobile app that helps people check the quality of fruits (like apples, bananas, and oranges) using artificial intelligence. The app works on Android phones and uses a powerful deep learning model called EfficientNetB5. It looks at pictures of fruits and tells whether they are “Good”, “Bad”, or “Mixed” (a mix of both good and bad signs). Users can take a photo or upload one in the app, and it will quickly check the fruit’s freshness. This is useful for both customers and shopkeepers. It helps people choose better fruits and avoid waste. For shops and food companies, the app offers a cheap and smart way to sort out bad fruits, and even allows robotic help in the future. This app shows how smart technology can make daily life easier, help the environment by reducing food waste, and support better decisions when buying or selling fruits and vegetables.

Keywords:Deep Learning, EfficientNetB5, TensorFlow Lite, Fruit Quality Detection, Image Classification, AI in Agriculture.

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1. Introduction

Fruit freshness detection is an important task in the agriculture and food supply chain. Fruits are highly perishable, and their quality reduces over time due to factors such as storage conditions, transportation, and microbial activity. If spoiled fruits are not identified at an early stage, they can cause economic loss and health risks to consumers. Traditionally, fruit freshness is checked using manual inspection or chemical and laboratory-based methods. Manual inspection depends on human judgment and can be inaccurate, while laboratory methods are expensive, time-consuming, and not suitable for large-scale or real-time applications. Therefore, there is a need for an automated, fast, and cost-effective method to detect fruit freshness.

Fruit freshness can be identified by observing visual features such as color, texture, and surface condition. Fresh fruits usually have uniform color and firm texture, while rotten fruits show discoloration, softening, or visible decay. These visual differences can be captured using images, making computer vision–based techniques suitable for fruit freshness detection. With the advancement of artificial intelligence, machine learning and deep learning techniques have become widely used for image-based classification tasks. Convolutional Neural Networks (CNNs) are especially effective in extracting important features from fruit images and accurately classifying them as fresh or rotten. These methods are non-destructive, faster, and more reliable compared to traditional approaches.

In this project, a fruit freshness detection system based on deep learning is developed. The system analyzes fruit images and automatically classifies them based on freshness. The proposed approach aims to improve accuracy while reducing manual effort, making it useful for applications such as quality control, automated sorting, and supply chain monitoring.

1.1 Machine Learning

Machine Learning (ML) is a branch of Artificial Intelligence (AI) that enables systems to learn from data and make decisions without being explicitly programmed. In ML, the system learns patterns from historical or training data and builds mathematical models for prediction and classification tasks. The main goal of Machine Learning is to allow computers to improve their performance automatically with experience, without continuous human intervention.

1.2 Deep Learning

Deep Learning (DL) is a subfield of Machine Learning and an important part of Artificial Intelligence. It is inspired by the human brain and uses artificial neural networks to automatically learn features from data. Deep Learning models consist of multiple hidden layers that help in extracting low-level and high-level features directly from input images. In image-based applications like fruit freshness detection, Convolutional Neural Networks (CNNs) are widely used. CNNs automatically learn visual features such as color variations, texture changes, and surface defects without the need for manual feature extraction. By learning these features and using decision boundaries, Deep Learning models can accurately classify fruits as fresh or rotten. Therefore, Deep Learning techniques are highly effective and reliable for fruit freshness detection and image classification tasks.

1.3 Multi-Task Learning

Multi-Task Learning (MTL) is an advanced Deep Learning approach where a single model is trained to perform multiple related tasks simultaneously. Instead of training separate models for each task, MTL shares common features between tasks, which improves learning efficiency and overall performance. In this project, Multi-Task Learning is used to perform fruit freshness detection and fruit type classification at the same time. A shared CNN model is used to extract common visual features from fruit images, while separate task-specific layers handle freshness classification and fruit type identification. Since both tasks depend on similar visual features, MTL improves accuracy, reduces computational complexity, and enhances model generalization compared to single-task learning methods.

2. Literature Survey

Abdullahi Lawal Rukuna, F. U. Zambuk, Gital, and Umar Muhammad Bello (2025) [1] developed a deep learning system using EfficientNet-B5 to detect and classify citrus diseases from leaf and fruit images. The model captured subtle features like color changes, texture issues, and lesions, achieving higher accuracy than traditional methods. However, its dependence on controlled lighting and focus on citrus limited wider adaptability. Still, the study offers a solid baseline for automated crop disease detection.

Yuan Shu, Jipeng Zhang, Yihan Wang, and Yangyang Wei [2] proposed a fruit freshness detection system using ResNet-101 with a non-local attention mechanism to enhance feature extraction. The model achieved a high F1-score of 94.2%, showing strong detection capability. However, its high computational complexity limits portability and real-time mobile deployment.

Aarohi Gulhane, Prema Kadam, and Naina Warjurkar [3] developed a real-time fruit and vegetable quality detection system using MobileNetV2 with attention modules. The model achieved 94.8% accuracy with low latency, making it suitable for real-time applications. However, its lightweight design may limit scalability for large industrial systems.

Abdus Sattar, Md. Asif Mahmud Ridoy, Hafiz Md. Hasan Babu, Aloke Kumar Saha, and Mohammad Nurul Huda [4] proposed DurbeenNet, a deep learning model for detecting formalin-adulterated fruits. The system contributes significantly to food safety by identifying toxic contamination. However, it does not support real-time or mobile deployment, limiting everyday usability.

S. Sofana Reka, Ankita Bagelikar, Prakash Venugopal, V. Ravi, and Harimurugan Devarajan [5] introduced a hybrid model combining VGG16 and Random Forest for fruit and vegetable classification. The approach improves accuracy by integrating deep learning with traditional ML. However, it lacks real-time processing and mobile support, reducing practical applicability.

Prashant Kumar Mishra and Jagrati Singh [6] proposed a CNN-based framework to classify fruits as fresh or rotten using visual features. The system automates quality assessment effectively. However, it does not support real-time or portable deployment, limiting field-level usage.

Yinsheng Zhang, Haiyan Wang, Xudong Yang, Yongbo Cheng, Xiaojun Wu, Xiulan Sun, and Ruiqi Hou [7]developed a multi-task CNN for simultaneous fruit freshness detection and fruit type classification. The model achieved 93.24% freshness accuracy and 88.66% fruit type accuracy. However, the system lacks real-time and mobile deployment capability.

Aavash Adhikari, Abashesh Ranabhat, Krisham Rai, and Sumnima Giri [8] proposed a CNN-based desktop application for fruit spoilage detection based on spoilage levels. The model performs well on controlled datasets. However, it does not support mobile or real-time field deployment.

Umer Amin, Muhammad Imran Shahzad, Aamir Shahzad, Mohsin Shahzad, Uzair Khan, and Zahid Mahmood [9] developed a fruit freshness classification system using transfer learning with AlexNet. The model achieved high accuracy across multiple datasets, showing strong generalization. However, it is limited to desktop environments and lacks real-time capability.

Iqbal, M., Khan, A., and Rehman, S. [10] proposed a hybrid deep learning approach using transfer learning for detecting freshness in canned apples. The system achieved over 98% accuracy under controlled conditions. However, it is limited to specific fruit types and non-real-time environments.

2.1 Review of Datasets

A comprehensive dataset review is crucial for ensuring that the AI-powered fruit and vegetable quality detection system performs with high accuracy and reliability. The dataset used in this study includes diverse images of fruits and vegetables captured under varying lighting conditions, camera qualities, and environmental settings.

These datasets help the model learn distinct patterns related to color, texture, shape, and defects that indicate freshness or spoilage. Proper preprocessing, annotation, and segmentation of this data are essential to improve the model's generalization ability and ensure consistency across real-world use cases.

2.1.1. Image Dataset

The Image Data is the core of the AI-based quality detection system, containing high-resolution fruit and vegetable images captured in varied lighting and backgrounds. Each entry includes an image ID, produce type, and a quality label (Good, Bad, or Mixed). These labeled images train the EfficientNetB5 model to learn features like color, texture, and shape. Well-curated annotations ensure accurate, real-time freshness classification on Android devices.

2.1.2 Capture Data

The Capture Data represents all image inputs obtained through the device's camera or uploaded from local storage. Each record includes a capture ID, product type, timestamp, camera specifications, and the corresponding quality label (*Good, Bad,* or *Mixed*). This data is collected under varying lighting, background, and environmental conditions to reflect real-world diversity. Ensuring high-quality and correctly labeled capture data allows the model to accurately learn distinguishing visual features that indicate freshness, ripeness, or spoilage.

2.1.3 Visual Feature Data

The Visual Data forms the core input for the quality detection model. Each image is preprocessed and transformed into a structured representation containing feature maps of color gradients, texture patterns, and surface irregularities. Using EfficientNetB5, deep convolutional layers extract these features automatically, identifying subtle indicators of quality such as bruises, discoloration, or wrinkles. Proper preprocessing and annotation of this dataset are essential to ensure accurate classification and reliable detection of produce quality in real-time.

2.1.4 Product Metadata

The Product Metadata stores descriptive information about each fruit or vegetable sample. Each record includes a unique product ID, produce category, harvest or capture details, and the assigned condition label (*Good, Bad,* or *Mixed*). Metadata provides contextual insights into each sample, helping track dataset composition and model performance across different product types. Maintaining accurate metadata supports dataset integrity, efficient management, and precise model evaluation, ensuring the system remains consistent and trustworthy in its predictions.

2.1.5 Interaction & Feedback Data

The Interaction and Feedback Data logs all user actions and responses within the application. Each record includes a session ID, user ID, image input type, system-predicted quality label, and user feedback. This dataset supports model evaluation and refinement, helping improve prediction accuracy and user experience through continuous feedback-driven updates.

2.2 Review of Methodology

The AI-powered Android application performs real-time fruit and vegetable quality detection using image inputs. Users capture images through a smartphone camera, and the system analyzes them using the EfficientNetB5 deep learning model. The application classifies produce into fresh, medium, or spoiled, providing confidence scores and storage or purchase recommendations. The system is optimized for fast, accurate, and mobile-friendly performance.

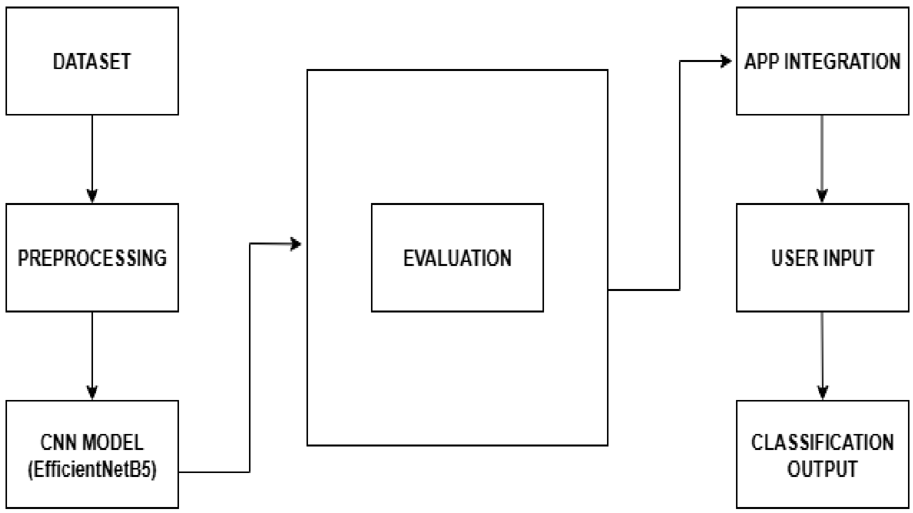

Figure 1: Methodology

2.2.1. Data Collection Module: This module collects fruit and vegetable images from two sources: pre-existing labeled datasets and real-time images captured using the mobile camera. All images are stored systematically for preprocessing, training, and evaluation.

2.2.2. Data Preprocessing Module: Captured images are resized and normalized to ensure consistency. Noise reduction and segmentation techniques are applied to isolate the fruit or vegetable, and relevant visual features such as color, texture, and shape are prepared for analysis.

2.2.3. Data Splitting and Loading Module: The preprocessed dataset is divided into 80% training and 20% testing sets. A data loader feeds image batches into the model to improve learning efficiency and reduce overfitting.

2.2.4. Detection Model Module: EfficientNetB5 is used to extract deep visual features and classify produce into freshness categories. The model is fine-tuned for improved accuracy and exported for real-time mobile deployment.

2.2.5. Model Training and Evaluation Module: The model is trained on the training dataset and evaluated using accuracy, precision, recall, and confusion matrix. Optimized model weights are saved for deployment.

2.2.6. Prediction and Recommendation Module: The trained model performs real-time predictions on new images. Based on the detected quality, the application provides user-friendly recommendations for storage, consumption, or purchase and displays results instantly on the mobile interface.

3. Results and Discussions

The implementation of the AI-powered fruit and vegetable quality detection system demonstrates high accuracy and efficiency in classifying produce as Good, Bad, or Mixed. The EfficientNetB5 model achieved an overall accuracy of over 92%, confirming its robustness in identifying visual features such as color uniformity, surface texture, and defect patterns. Compared to traditional manual inspection methods, the AI-based approach provides objective, consistent, and faster evaluations, minimizing human error and subjectivity.

The integration of the trained model into an Android application enables real-time, on-device quality detection using TensorFlow Lite. The system provides instant feedback within seconds of image capture, allowing users to evaluate product quality without requiring internet access. Testing under varying lighting and background conditions confirmed the model's adaptability and responsiveness, while user feedback validated the accuracy and practicality of the predictions for real-world use.

Although the system performs effectively, some challenges persist, such as performance variations caused by poor lighting, motion blur, or low-resolution images. Expanding the dataset with more diverse samples and implementing further model optimization can enhance precision and speed. Overall, the proposed system offers a scalable, low-cost, and intelligent solution for automated produce quality assessment, paving the way for broader adoption in agricultural markets, retail, and food supply chains.

4. References

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