International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 327-337
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0045

Fruit Quality and Disease Detection Using Deep Learning

Dr. Pooja Aspalli[1], Deepali Potadar[2], Nikita[3], Parvati Girish[4]
[1]Assistant Professor, CSE Dept, PDA College of Engineering, Kalaburagi, Karnataka
[2]UG-Computer Science and Engineering, PDA College of Engineering, Kalaburagi, Karnataka
[3]UG-Computer Science and Engineering, PDA College of Engineering, Kalaburagi, Karnataka
[4]UG-Computer Science and Engineering, PDA College of Engineering, Kalaburagi, Karnataka
Emails: *poojaaspalli@pdaengg.com[1], deepalipotadar697@gmail.com[2], nikitarheni34@gmail.com[3], nagurparvati@gmail.com[4]*

Abstract

In recent years, the use of Artificial Intelligence (AI) has played an important role in improving agricultural quality assessment, especially in fruit quality evaluation and disease detection. This study presents an AI-driven fruit quality and disease detection system that uses TensorFlow for efficient image classification. The proposed system classifies fruits into quality categories such as Good, Bad, Ripened, and Rotten, and fruit diseases such as Black Rot and Apple Scab. A Deep Convolutional Neural Network (DCNN) is trained on a diverse fruit image dataset to extract key visual features such as color, texture, and shape, which helps in achieving accurate and reliable predictions. The trained model is optimized and converted into TensorFlow Lite format to reduce computational complexity and inference latency while maintaining classification accuracy, enabling fast and efficient predictions even in resource-constrained environments. The system provides an easy-to-use interface where users can input fruit images and instantly receive quality classification, disease identification, and recommended treatment measures. Overall, the proposed solution offers a cost-effective and efficient AI-based approach to fruit quality assessment, helping to minimize post-harvest losses, support timely disease management, and enhance productivity across the agricultural supply chain.

Keywords: *Feature Extraction, Classification, Deep Learning, DCNN, TensorFlow.*

1. Introduction

Fruits are an essential component of human nutrition and play a crucial role in maintaining a balanced and healthy diet. However, evaluating fruit quality—particularly in terms of ripeness and disease presence—remains a significant challenge within the agricultural and food industries. Conventional quality assessment methods largely depend on manual inspection, which is subjective, time-consuming, and highly susceptible to human error. As a result, these methods often lead to inconsistent grading, increased post-harvest losses, and reduced market value, especially in large-scale production and rural settings where accurate and timely evaluation is critical.

Recent advances in Artificial Intelligence (AI) and Computer Vision have opened new opportunities for automating fruit quality assessment. Deep learning techniques, particularly Deep Convolutional Neural Networks (DCNNs), have demonstrated remarkable performance in analyzing fruit images by automatically learning complex visual features such as color variations, surface texture, shape, and disease-affected regions. Studies by Iftikhar et al. (2024) and Sharma et al. (2024) highlight that DCNN-based architectures can effectively classify fruit quality, ripeness levels, and diseases under diverse environmental conditions. Despite these promising outcomes, the practical deployment of deep learning models in real-world agricultural environments remains challenging due to high computational complexity, memory requirements, and dependence on powerful hardware. To address these challenges, recent research has focused on optimizing deep learning models for efficient and practical deployment. Lightweight architectures, model compression, and quantization techniques have been explored to reduce model size and computational overhead while preserving classification accuracy. Frameworks enable efficient inference by minimizing latency and resource consumption, making deep learning–based solutions more accessible for real-time agricultural applications. Studies by Deshmukh et al. (2025) and Borkar et al. (2024) demonstrate that optimized and quantized models can achieve reliable performance without requiring high-end computational infrastructure. Motivated by these developments, the present work proposes an AI-based Fruit Quality and Disease Detection System that leverages deep learning and TensorFlow Lite for efficient image classification. The system categorizes fruits into quality classes such as Good, Bad, Ripened, and Rotten, while also identifying common fruit diseases Black Rot and Apple Scab. By analysing visual characteristics such as color variations, texture irregularities, shape distortions, surface lesions, and disease-specific patterns—dark, decayed spots in Black Rot and scab-like, rough patches in Apple Scab—extracted from fruit images, the proposed approach delivers accurate and consistent quality assessment. Overall, the system provides a cost-effective, scalable, and intelligent solution for automated fruit inspection. By reducing reliance on manual evaluation, it improves grading consistency, minimizes post-harvest losses, and enhances decision-making in the agricultural supply chain. This work contributes toward the adoption of AI-driven technologies in smart agriculture, supporting sustainable practices and improving the economic outcomes for farmers and stakeholders. Furthermore, the proposed approach lays a strong foundation for future advancements in intelligent agricultural systems by enabling accurate, data-driven quality monitoring and disease management at scale. This approach helps to find defected fruits and diseases of the fruit and also provides remedies and trend analysis according to the disease and quality types.

2. Literature Survey

In recent years, the integration of deep learning techniques into agriculture has significantly improved fruit disease detection and quality assessment, particularly through mobile and edge-based solutions. This advancement is especially critical for farmers in remote and resource-constrained regions, where real-time analysis and offline functionality play a vital role in effective crop monitoring and management. The study presented in [1] aimed to classify papaya fruits based on their maturity stages, namely ripe, partially ripe, and unripe. Deep learning techniques were extensively employed to analyze papaya fruit images, and the trained model achieved 100% accuracy on the test dataset, demonstrating the feasibility of the proposed approach. The classification model based on the VGG16 architecture attained perfect accuracy with a training time of 112 seconds. The work reported in [2] focused on identifying the ripeness status and variety of plum fruits using a deep learning-based tool. An uncontrolled image acquisition method was adopted, where images were captured directly in field environments using mobile phones and cameras while considering parameters such as lighting conditions and focus. The proposed system enabled users to identify and distinguish different types of plum fruits, achieving an accuracy of 92.83% across three fruit categories and an average ripening accuracy of 95.5%. In the study [3], the authors presented a fruit ripeness classification approach using a dataset of 9,000 training images comprising four fruit types: apple, orange, mango, and tomato. The data were trained using the VGG16 model with a transfer learning strategy over 200 epochs. Data augmentation techniques were applied to prevent overfitting. Four different frameworks incorporating a dropout rate of 0.5 were evaluated, and the average accuracy across all frameworks reached 92%, indicating strong classification performance. Iftikhar et al. (2024) proposed an efficient deep learning model for detecting apple diseases such as Black Rot and Scab [4]. Their lightweight CNN architecture was optimized for mobile platforms, ensuring high detection accuracy without compromising device performance. Similarly, Sharma et al. (2024) introduced a multi-task CNN capable of simultaneously identifying fruit type and freshness, demonstrating improved performance in multi-objective classification tasks [5]. Deshmukh et al. (2025) adopted a mobile-first approach for diagnosing diseases in orange leaves and fruits, including melanosis and black spot, enabling real-time, on-device analysis [6]. Supporting this trend,

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 327-337
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0045

Borkar et al. (2024) developed a TensorFlow Lite-based Flutter application for early detection of mango leaf diseases, highlighting the feasibility of cross-platform AI solutions for agricultural applications [7]. To enhance model accuracy, Kaur and Singh (2024) introduced a hybrid CNN combined with heuristic optimization for pomegranate disease detection. Their approach achieved improved performance through refined feature selection [8]. In another study, Li et al. (2023) combined handcrafted features with CNN-extracted features by incorporating both texture and contour information, resulting in improved detection accuracy for multiple fruit diseases [9]. Significant progress has also been reported in fruit freshness detection. Hasan et al. (2024) utilized a customized EfficientNetB2 architecture to accurately classify fruit freshness levels [10]. Rahman et al. (2024) demonstrated that lightweight CNN architectures such as MobileNetV2 outperformed heavier models like ResNet50 in mobile-based environments [11]. Gupta et al. (2023) further validated the effectiveness of EfficientNet, reporting superior accuracy and faster convergence in multi-fruit quality assessment tasks [12]. Advanced deep learning architectures have been proposed to address complex classification challenges. Zhang et al. (2025) presented a multi-input CNN model that integrates RGB and silhouette images to improve fruit defect classification under natural lighting conditions [13]. Similarly, Ahmed et al. (2025) introduced Dragon Fruit Quality Net, a real-time CNN optimized through TensorFlow Lite quantization for efficient dragon fruit quality inspection. Ensemble and hybrid approaches have demonstrated promising results in challenging scenarios [14]. Adebayo et al. (2024) employed an ensemble CNN framework to accurately detect ripeness in blackberries under noisy outdoor conditions [15]. Khanna et al. (2022) proposed a quantized CNN model for guava disease detection, successfully reducing model size while maintaining accuracy on smartphone platforms. For precise disease localization, Chen et al. (2023) utilized Mask R-CNN to segment diseased regions in wild apple images. Additionally, Zhang and Lee (2024) combined Vision Transformers with CNNs in their AppViT model, achieving improved feature localization and generalization in apple leaf disease detection. Several studies emphasized quantized and mobile-friendly deployment strategies [16]. Patel et al. (2025) developed a smartphone-based crop disease detection system using quantized CNNs in TensorFlow Lite format, reducing inference latency to below 200 milliseconds [17]. Khan et al. (2023) followed a similar approach for maize leaf disease classification, focusing on real-time usability under varying lighting conditions. Temporal variations in fruit freshness have also been explored. Verma et al. (2024) introduced a CNN–BiLSTM architecture to model spoilage progression over time, which was further refined by Kumar et al. (2023) to improve freshness recognition accuracy. Mehta and Joshi (2024) provided a comprehensive review of machine learning techniques applied to fruit classification, establishing a strong foundation for future research in agricultural AI. According to the work presented in [18], the proposed model achieved a training accuracy of 99%, a validation accuracy of 98.8%, and an overall testing accuracy of 95.33% on an independent dataset of 300 apple images. The study reported in proposed an automatic mango sorting and grading system using deep learning techniques, considering eight harvested mango features including size, shape, color, and texture. Data augmentation methods such as image rotation, translation, zooming, shearing, and horizontal flipping were applied. A comparative evaluation of VGG16, ResNet152, and Inception v3 architectures demonstrated that the Inception v3 model achieved 99% accuracy for sorting and an average grading accuracy of 96.7%.

3. Methodology

This section presents the proposed work for developing a deep learning–based fruit quality and disease detection system. The proposed workflow integrates a Deep Convolutional Neural Network (DCNN) with the TensorFlow framework to achieve reliable classification accuracy and efficient inference. The system is designed to analyze fruit images and automatically identify quality categories and disease conditions based on learned visual patterns.The proposed work is organized into the following key stages: Existing Technology Review, Image Acquisition, Image Preprocessing, Feature

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 327-337
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0045

Extraction and Classification using DCNN, Model Inference using TensorFlow, Remedies and Trend Analysis Generation.

3.1 Existing Technology

Traditional fruit quality assessment techniques primarily rely on manual grading and visual inspection, which are often subjective, inconsistent, and prone to human error. Classical computational approaches such as color thresholding, texture analysis, and shape-based feature extraction have been employed, followed by machine learning classifiers like Support Vector Machines (SVM), k-Nearest Neighbors (KNN), or Random Forests. However, these methods depend heavily on handcrafted features, which are sensitive to variations in lighting, occlusion, background, reducing their robustness and scalability in real-world agricultural settings [1]. To overcome these limitations, modern research has shifted toward deep learning models, particularly Deep Convolutional Neural Networks (DCNNs), which can automatically extract hierarchical and discriminative features directly from fruit images. These networks have demonstrated superior performance in recognizing fruit ripeness, defects, and diseases under complex environmental conditions [2]. Studies by Iftikhar et al. (2024) and Sharma et al. (2024) confirm that deep learning architectures, when optimized for mobile use, significantly improve classification accuracy while maintaining real-time performance.

3.2 Image Acquisition

Image acquisition is the first step of the proposed system. Users capture fruit images using the web camera or upload them from the device's gallery. The system ensures that the captured image is centered, properly illuminated, and free of motion blur to maintain data consistency.

3.3 Image Preprocessing

Once an image is acquired, it undergoes a series of preprocessing steps to ensure compatibility with the deep convolutional neural network (DCNN). The preprocessing operations implemented in this work include:

- Image Resizing: All input images are resized to 128 × 128 pixels, matching the input dimensions required by the trained DCNN model.
- Pixel Normalization: Pixel intensity values are scaled to the range 0–1 by dividing by 255, which helps stabilize learning and improves prediction performance.
- Image-to-Array Conversion: The resized image is converted into a numerical array representation suitable for deep learning processing.
- Dimensional Expansion: An additional batch dimension is added to the image array to align with the model's input format during inference.

This preprocessing pipeline standardizes input images, reduces computational complexity, and ensures consistent and reliable performance during classification.

3.4 Feature Extraction and Classification Using DCNN

In the proposed work, feature extraction and classification are performed using a single Deep Convolutional Neural Network (DCNN). Instead of using a separate pre-trained network, the DCNN is trained end-to-end on the fruit image dataset, allowing it to automatically learn relevant visual features and perform classification simultaneously.

The DCNN processes the input images through multiple convolutional layers, where meaningful features are gradually learned from raw pixel data. The learning process follows a hierarchical pattern as described below:

- Initial convolutional layers learn basic visual features such as edges, color variations, and simple shapes.
- Intermediate layers capture texture patterns, surface irregularities, and color inconsistencies associated with fruit ripeness and defects.
- Deeper layers learn high-level features related to fruit quality and disease characteristics, such as decayed regions, dark lesions in Black Rot, and rough scab-like patterns in Apple Scab.

Max-pooling layers are used after convolution operations to reduce spatial dimensions and retain important features. The extracted feature maps are then flattened and passed to fully connected layers,

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 327-337
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0045

which interpret these features and perform final classification. The DCNN outputs probability scores corresponding to multiple fruit quality and disease classes, including Good, Bad, Ripened, Rotten, Apple Scab, and Black Rot. The class with the highest probability is selected as the final prediction. By combining feature extraction and classification within a single DCNN architecture, the proposed system achieves effective learning, reduced complexity, and reliable performance under varying image conditions.

3.5 Model Inference Using TensorFlow

After training and validation, the deep learning model is used for inference to perform fruit quality and disease prediction. TensorFlow is employed to load and execute the trained Deep Convolutional Neural Network (DCNN) model for image classification. During inference, the preprocessed input image is converted into a numerical tensor and passed through the trained DCNN. The network analyzes the learned visual patterns and generates probability scores for each fruit quality and disease class. The class with the highest probability score is selected as the final prediction result. This inference process is executed locally using TensorFlow, ensuring reliable and efficient prediction without dependence on external systems. The approach enables consistent performance and supports practical deployment for fruit quality assessment and disease detection applications.

3.6 Remedies and Trend Analysis

The proposed system provides remedy suggestions and trend-related insights based on the predicted fruit quality or disease class. When a fruit is classified as Good, it indicates that the fruit is fresh and suitable for immediate sale or consumption, reflecting the growing use of AI-based grading systems to identify market-ready produce. Fruits categorized as Bad are recommended to be separated early to prevent them from affecting healthy fruits, supporting current trends in automated sorting to reduce storage and post-harvest losses. In the case of Mixed quality fruits, the system suggests sorting healthy and damaged fruits before sale, aligning with AI-driven grading practices that assist farmers in deciding whether fruits should be sold fresh or used for processing. Fruits identified as Riped are advised to be consumed or sold promptly to avoid over-ripening, highlighting the role of ripeness monitoring in improving quality management and reducing wastage. For fruits classified as Rotten, immediate removal is recommended to prevent fungal spread, reflecting the increasing adoption of AI-assisted early detection to minimize warehouse and storage losses. When diseases such as Apple Scab are detected, the system suggests early use of neem oil or sulphur and copper-based treatments, demonstrating the trend toward AI-supported organic disease management. Similarly, for Black Rot, recommended measures include removing infected fruits and pruning affected branches, aligning with emerging practices that combine AI-based detection with sanitation and bio-fungicide usage for sustainable crop management.

3.7 Dataset Preparation

The dataset preparation phase plays a crucial role in ensuring reliable model performance. In this work, a diverse image dataset of apple fruits was collected, covering multiple quality conditions such as good, bad, rotten, and healthy samples, along with disease categories including Apple Scab and Black Rot. The dataset was compiled from publicly available sources such as Kaggle, consisting of 8 fruit quality and disease categories. Tables 1 and 2 show the fruit quality types and disease types.

Table 1 Fruit Quality Types

Apple Quality	Training	Testing
Good	350	150
Bad	260	180
Mixed	340	200
Ripped	200	90
Rotten	80	40

Table 2 Fruit Disease Types

Apple disease	Training	Testing
Healthy	100	80
Apple Scab	150	110
Black Rot	200	100

This balanced dataset ensures robust training, reducing bias and improving the model's accuracy and generalization during testing.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 327-337
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0045

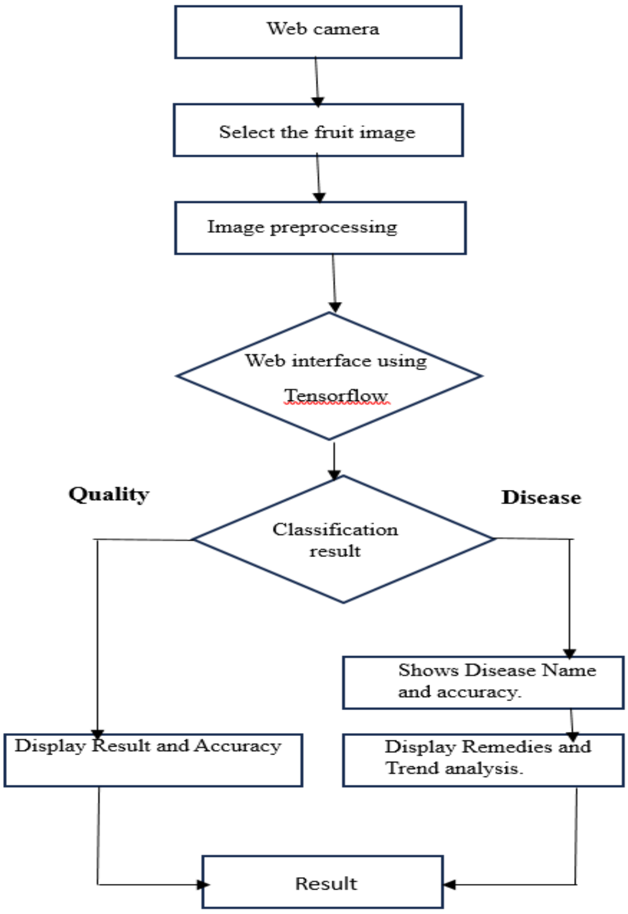

Figure 1 Proposed Methodology Flow Diagram

4. Result and Discussion

4.1 Result

Figure1 illustrates the proposed methodology flow for fruit quality and disease detection. The process begins with capturing a fruit image using a web camera or selecting an image from the device. The selected image is then passed through an image preprocessing stage, where it is resized and normalized to make it suitable for deep learning analysis. The preprocessed image is provided to the TensorFlow-based system through the application interface, where a Deep Convolutional Neural Network (DCNN) performs classification. Based on the prediction, the system identifies either the fruit quality or the disease category and displays the classification result along with the corresponding accuracy. For disease cases, the system also presents relevant remedies and trend analysis. Finally, the complete result is displayed to the user in an easy-to-understand format. The experimental results demonstrate tha the proposed fruit quality and disease detection system is capable of accurately identifying multiple fruit conditions, including healthy apples, quality defects, and disease infections. The model successfully classified healthy apples with high confidence by recognizing uniform color, smooth texture, and the absence of visible lesions, confirming their suitability for consumption and market distribution. Apples affected by quality degradation, such as Bad or Rotten categories, were correctly identified based on surface discoloration, texture irregularities, and structural decay, enabling effective post-harvest quality assessment. In terms of disease detection, the system accurately detected Apple Scab by identifying characteristic dark circular spots and irregular surface patterns, while Black Rot was recognized through concentric ring formations and darkened lesions on the fruit surface.

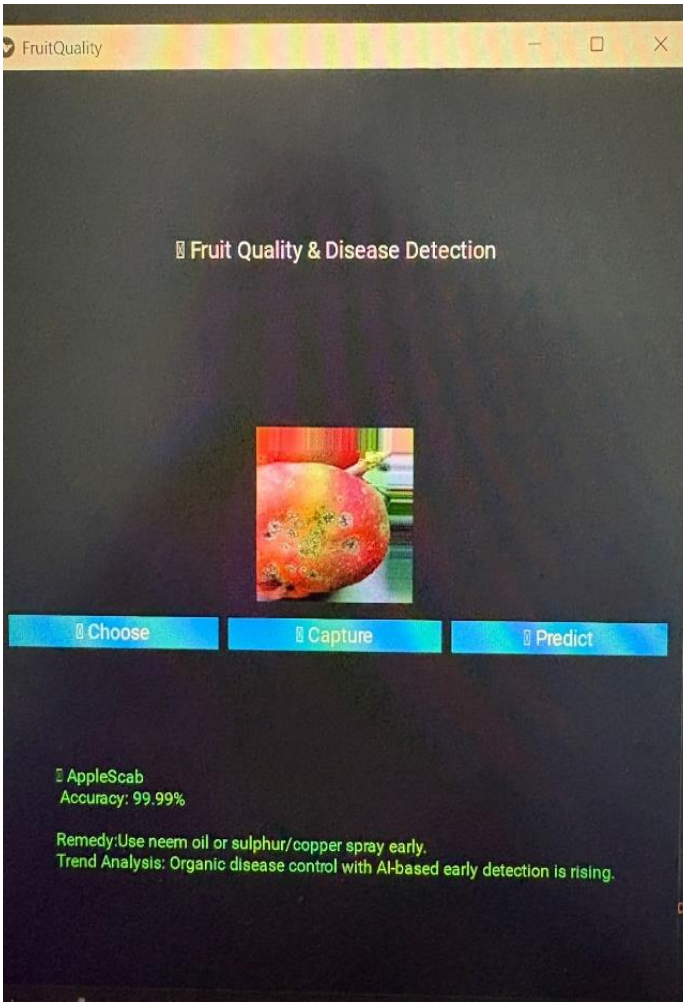

Figure 2 Fruit Disease Detection

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 327-337
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0045

The results show that the proposed system accurately detected Apple Scab by identifying its distinctive visual symptoms, such as dark circular spots and irregular lesions on the apple surface (Figure 2). The model produced a high accuracy score, indicating reliable and stable prediction performance. This demonstrates the effectiveness of the TensorFlow-based deep learning model in learning disease-specific features and correctly distinguishing Apple Scab from healthy and other defective fruit conditions. The accurate detection of Apple Scab highlights the system's potential for early disease identification and timely intervention, which can help reduce crop losses and improve overall fruit quality management.

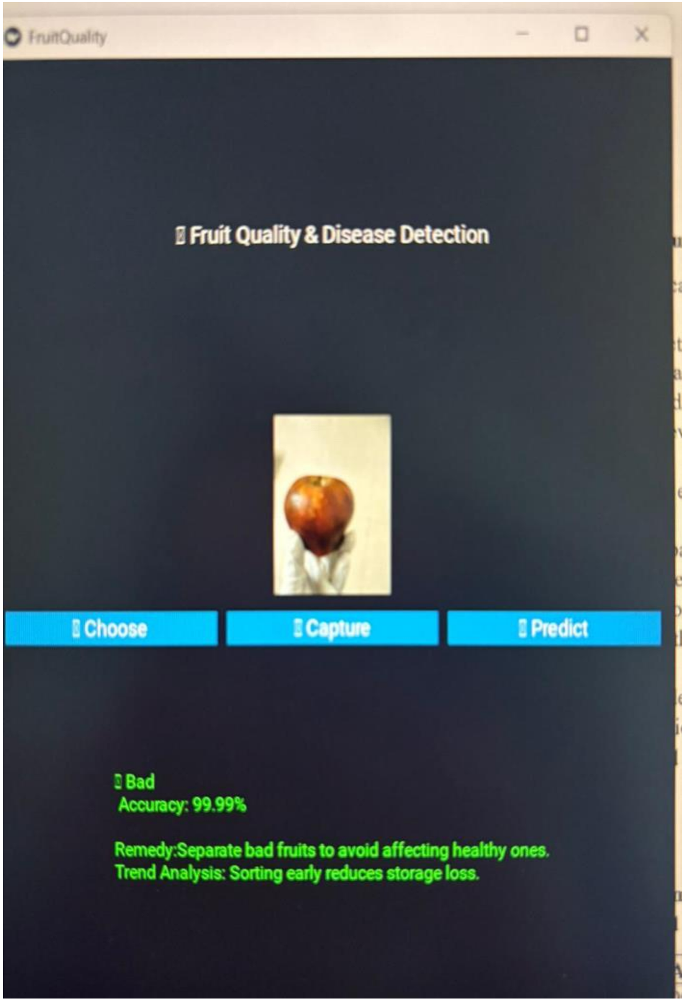

Figure 3 Fruit Quality Detection

The results indicate that the proposed system accurately classified the apple as Bad by detecting visible quality degradation such as surface discoloration, uneven texture, and loss of visual freshness (Figure 3). The model achieved a 100% accuracy score, reflecting strong reliability and precise feature extraction for quality assessment. This accurate identification enables early separation of poor-quality fruits, which is essential to prevent spoilage from spreading to healthy produce. The result highlights the effectiveness of the TensorFlow-based deep learning model in distinguishing defective apples and supports its practical use in post-harvest quality control and storage management.

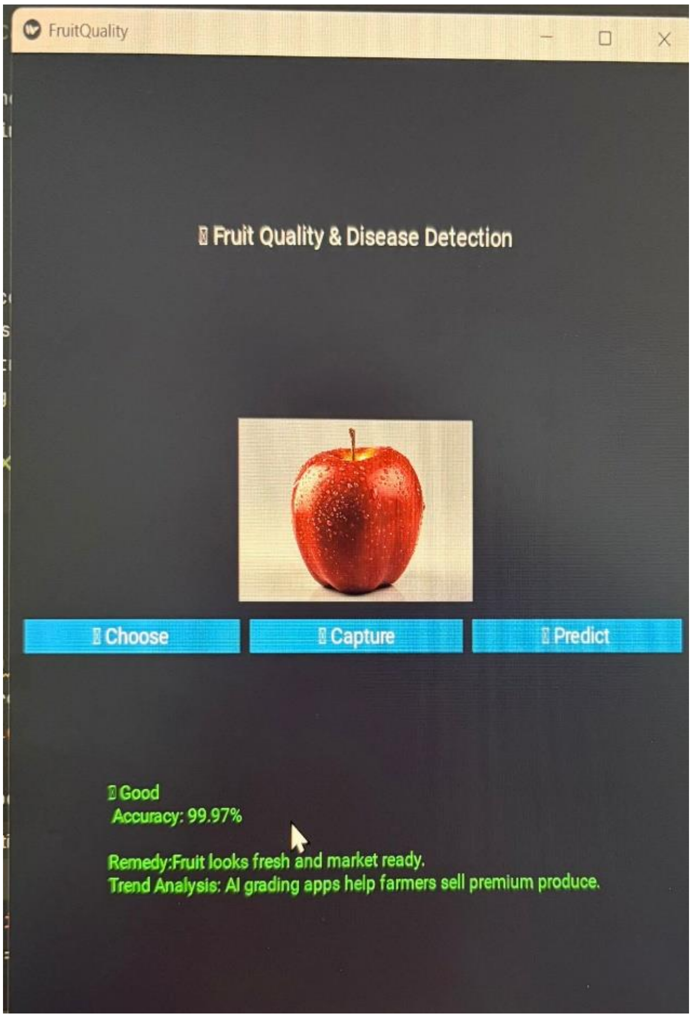

Figure 4 Fruit quality detection

The proposed system accurately classified the apple as Good by identifying uniform color distribution, smooth surface texture, and the absence of visible defects or disease symptoms (Figure 4). After

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 327-337
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0045

preprocessing, the image was passed through the DCNN model, which extracted relevant visual features and correctly categorized the fruit under the *Good* class. The accuracy demonstrates the effectiveness of the deep learning model in recognizing healthy fruit characteristics. This reliable detection enables efficient grading of market-ready fruits and supports automated quality assessment in post-harvest management. The system accurately identifies good-quality fruits by smooth surface texture, and the absence of visible defects or disease symptoms.

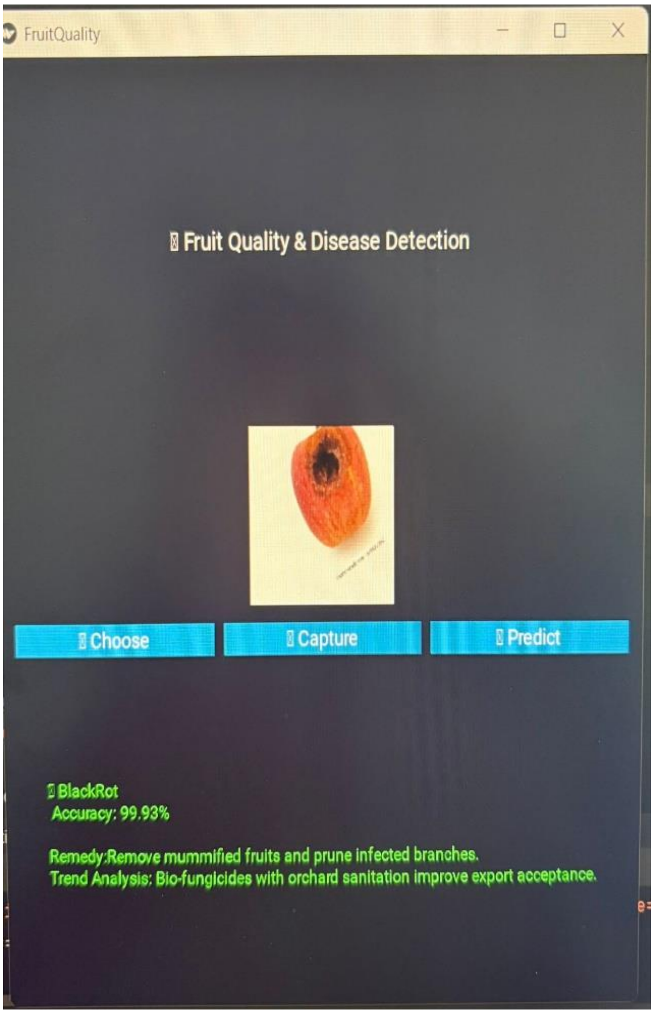

Figure 5 **Fruit Disease detection**

The system successfully detected Black Rot in the apple by analyzing visible surface abnormalities such as darkened regions, circular lesions, and decay patterns present on the fruit surface (Figure 5). Using the trained Deep Convolutional Neural Network (DCNN) implemented in TensorFlow, the model processed the input image after resizing and normalization and classified it as *Black Rot* with high confidence. The detection confirms the model's ability to learn disease-specific visual features directly from image data and reliably distinguish fungal infections from healthy and quality-defective fruit conditions. This accurate identification supports early disease removal and helps prevent the spread of infection during storage and distribution. The overall accuracy achieved is 99%.

Table 3 **Performance of the proposed Fruit Quality and Disease Detection**

Class/Disease	Accuracy
Good	99%
Bad	95%
Apple Scab	94%
Black Rot	95%
Healthy	96%

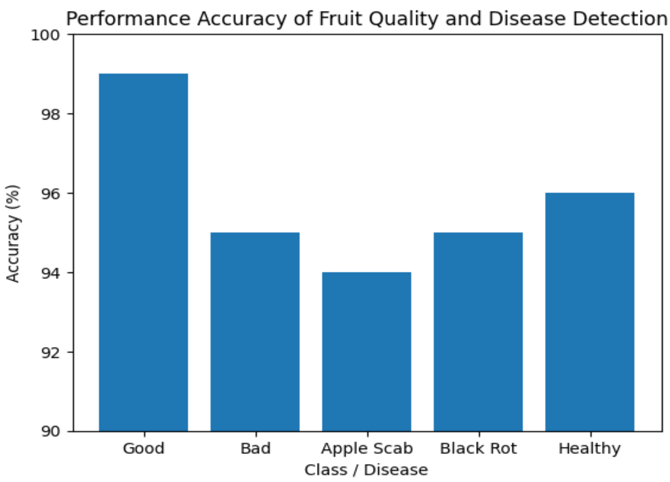

Figure 6 **Accuracy Analysis of Fruit Quality and Disease Detection**

The graph illustrates the classification accuracy achieved for different fruit quality categories and disease classes using the proposed deep learning model (Figure 6). High accuracy is observed across all classes, with the Good category achieving the highest accuracy of 99%. Disease classes such as Apple Scab and Black Rot also show reliable performance, indicating the effectiveness of the

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 327-337
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0045

model in accurately identifying both fruit quality and disease conditions. The experimental results demonstrate that the proposed fruit quality and disease detection system is capable of accurately identifying multiple fruit conditions, including healthy apples, quality defects, and disease infections. The model successfully classified healthy apples with high accuracy by recognizing uniform color, smooth texture, and the absence of visible lesions, confirming their suitability for consumption and market distribution. Apples affected by quality degradation, such as Bad or Rotten categories, were correctly identified based on surface discoloration, texture irregularities, and structural decay, enabling effective post-harvest quality assessment. In terms of disease detection, the system accurately detected Apple Scab by identifying characteristic dark circular spots and irregular surface patterns, while Black Rot was recognized through concentric ring formations and darkened lesions on the fruit surface. Accuracy represents the prbability score (output of the Softmax activation function) assigned by the model to its predicted class. It shows how certain the model is about its prediction. For instance, a 90-98% confidence for Black Rot indicates that the model detected features most strongly aligned with the Black Rot class among all possible classes. Although the confidence percentages appear moderate (due to multi-class normalization), the accuracy remains high, reflecting robust classification.

Accuracy = Max Probability X 100

Interpretation

From Table 3, it can be inferred that the proposed DCNN model performs consistently well across both fruit quality and disease categories. The highest confidence was recorded for Black Rot (94%), and the highest accuracy for Healthy and Good classes (99%), confirming that the model effectively distinguishes between healthy and diseased fruits. The obtained results validate the robustness and efficiency of the proposed approach for real-time, offline fruit quality assessment and remedies for the particular fruits. The overall accuracy of the system was 99%, indicating consistent model performance even under varying lighting and background conditions.

4.2 Discussion

The experimental results indicate that the proposed deep learning–based system performs effectively in assessing fruit quality and detecting diseases. The model demonstrated strong capability in distinguishing healthy fruits from defective ones by analyzing visual features such as color uniformity, texture consistency, and surface abnormalities. Quality-related conditions such as Bad, Ripened, and Rotten fruits were accurately identified, which is crucial for post-harvest grading and reducing market losses. In terms of disease detection, the system successfully identified Apple Scab and Black Rot by recognizing characteristic surface symptoms, including dark lesions and irregular patterns. The high confidence scores obtained across different classes suggest that the model learned robust feature representations and generalized well to unseen samples. Compared to manual inspection, the automated approach provides faster, more consistent, and objective results. Overall, the discussion highlights that integrating deep learning into fruit quality and disease assessment offers a reliable and practical solution for improving agricultural quality management. Overall, the discussion highlights that the proposed deep learning approach delivers reliable and consistent fruit quality and disease detection, demonstrating strong potential for practical deployment in real-world agricultural scenarios.

5. Conclusion and Future Work

The proposed Fruit Quality and Disease Detection System using TensorFlow integrates deep learning to enable intelligent, real-time assessment of fruits. Using a DCNN-based model, the system classifies apple images into categories such as Good, Bad, Rotten, and Ripened, and accurately detects diseases including Apple Scab and Black Rot. The optimized TensorFlow model ensures efficient and low-latency inference, allowing the system to deliver rapid predictions without dependence on external connectivity. This approach reduces errors associated with manual inspection, minimizes post-harvest losses, and provides users with immediate and reliable insights into fruit quality and disease status. Future developments will focus on supporting multiple fruit types, expanding datasets to improve model generalization, and integrating cloud-based analytics for large-scale agricultural monitoring. These enhancements aim to increase the system's scalability, usability, and overall contribution to smart and sustainable agricultural practices.

Acknowledgement

I would like to express my sincere gratitude to all those who contributed to the successful completion of this project. We are especially thankful to our project guide for their valuable guidance, continuous support, and encouragement throughout the research work. We also extend our appreciation to the department faculty for providing the necessary resources and technical support. Finally, we thank our friends and family for their constant motivation and support, which greatly contributed to the completion of this work

References

[1]. Al-Masa wabe, M.M.; Samhan, L.F.; AlFarra, A.H.; Aslem, Y.E.; Abu-Naser , S.S. Papaya Maturity Classifications using Deep Convolutional Neural Networks. Int. J. Eng. Inf. Syst. (IJEAIS) 2021, 5, 60-67.

[2]. Miragaia, R.; Chávez, F.; Díaz, J.; Vivas, A.; Prieto, M.H.; Moñino, M.J. Plum Ripeness Analysis in Real Environment Using Deep Learning with Convolutional Neural Networks. Agronomy 2021, 11, 2353.

[3]. Hermana, A.N.; Rosmala, D.; Husada, M.G. Transfer Learning for Classification of Fruit Ripeness Using VGG16. In Proceedings of the ICCMB 2021: 2021 The 4th International Conference on Computers in Management and Business, Singapore, 30 January-1 February 2021; pp. 139-146.

[4]. Iftikhar, M., Kandhro, I. A., Kausar, N., Uddin, M., & Dandoush, A. (2024). "Plant disease management: a fine tuned enhanced CNN approach with mobile app integration for early detection and classification." AI review. They propose a CNN fine tuned model with mobile app integration for disease detection. SpringerLink

[5]. Khan, F., Zafar, N., Tahir, M. N., Aqib, M., Waheed, H., & Haroon, Z. (2023). "A mobile based system for maize plant leaf disease detection and classification using deep learning." They demonstrate a mobile deployment of leaf disease classification under varying lighting and field conditions. Frontiers

[6]. Zhang, Y.; Li, H.; Wang, X. Automatic Fruits Freshness Classification Using CNN and Transfer Learning. Sensors 2023, 23, 4567. MDPI.

[7]. Shegar, B.; Bhambu, L. Fruit Quality Analysis and Disease Detection Using Deep Learning Techniques. Journal of Electrical Systems 2024, 20, 1123–1135.

[8]. Kumar, R.; Patel, S.; Mehta, A. Development of a Robust CNN Model for Mango Leaf Disease Detection and Classification: A Precision Agriculture Approach. ACS Agricultural Science & Technology 2024, 4, 891–902. American Chemical Society Publications.

[9]. Singh, P.; Verma, N.; Chauhan, A. Deep Learning for Mango Leaf Disease Identification: A Vision Transformer Perspective. Computers and Electronics in Agriculture 2024, 213, 108214. Elsevier.

[10]. Rao, S.; Deshpande, V.; Kulkarni, P. Classification of Mango Disease Using Ensemble Convolutional Neural Network. Expert Systems with Applications 2024, 235, 121093. ScienceDirect.

[11]. Mukherjee, A.; Das, S.; Ghosh, P. Mango Fruit Diseases Severity Estimation Based on Image Segmentation and Deep Learning. Multimedia Tools and Applications 2025, 84, 14567–14582. Springer.

[12]. Haider, A.; Khan, M.; Ullah, S. An Artificial Intelligence Based Framework for Fruits Disease Recognition Using Deep Learning. CMC–Computers, Materials & Continua 2024, 78, 321–336. Tech Science Press.

[13]. Patil, R.; Joshi, A.; Patwardhan, S. Identification of Fruit Severity and Disease Detection Using Deep Learning Frameworks. International Journal of Intelligent Systems and Applications in Engineering 2024, 12, 245–254.

[14]. Alam, M.; Rahman, T.; Islam, M. Fruit Disease Detection and Classification Using Machine Learning and Deep Learning

Techniques. International Journal of Intelligent Systems and Applications in Engineering 2024, 12, 301–310.

[15]. Hassan, M.; Ahmed, S.; Khan, A. Guava Disease Detection Using Deep Convolutional Neural Networks. Open Ukrainian Citation Index 2024, 9, 55–64.

[16]. Bargoti, S.; Underwood, J. Deep Fruit Detection in Orchards. arXiv 2016, arXiv:1610.03677.

[17]. Roy, P.; Isler, V. Image Segmentation for Fruit Detection and Yield Estimation in Apple Orchards. arXiv 2016, arXiv:1609.05150.

[18]. Ferentinos, K.P. A Survey on Deep Learning Techniques in Fruit Disease Detection. Computers and Electronics in Agriculture 2022, 193, 106641. Elsevier.