IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A DEEP LEARNING AND IMAGE PROCESSING INTEGRATED MODEL FOR REAL TIME PREDICTION OF FRUIT QUALITY IN AGRICULTURAL SUPPLY CHAINS

[1]Aishwarya G Kulkarni,[2]Annapurna, [3]Ashrita P Partabad, [4]Bhagyashree, [5]Siddaling

[1-4]Students, [5]Assistant Professor

[1-5]Computer Science & Engineering,

[1-5]Sharnbasva University,Kalaburagi,Karnataka,India

Abstract: Fruit quality plays a crucial role in consumer satisfaction, food safety, market value, and supply chain efficiency. Traditional fruit quality assessment methods rely heavily on manual inspection, which is time-consuming, subjective, and prone to inconsistencies. This study presents a deep learning and image processing integrated model for real-time prediction of fruit quality in agricultural supply chains. The proposed framework combines InceptionResNetV2-based image classification with YOLOv11 real-time object detection to accurately identify and categorize fruits according to their quality conditions. The system processes fruit images through preprocessing techniques, feature extraction, and automated classification to detect good, bad, and mixed quality categories across multiple fruit types, including apples, bananas, guavas, limes, oranges, and pomegranates. A Flask-based web application enables image upload, live camera detection, prediction visualization, and database-driven result management. The integration of deep learning algorithms with computer vision techniques enhances prediction accuracy, operational efficiency, and decision-making capabilities. Experimental evaluation demonstrates reliable performance under diverse conditions, supporting automated quality monitoring, reducing human intervention, minimizing post-harvest losses, and improving overall agricultural supply chain productivity and sustainability.

Index Terms –Fruit Quality Assessment, Deep Learning, Image Processing, YOLOv11, InceptionResNetV2, Computer Vision, Real-Time Detection, Agricultural Supply Chain, Flask, Fruit Classification.

I. Introduction

Agriculture remains one of the most important sectors supporting food security, economic growth, and global trade. The increasing demand for fresh and high-quality agricultural produce has encouraged the adoption of advanced technologies that improve efficiency, accuracy, and decision-making throughout supply chains. Among various agricultural products, fruits require special attention because they are highly perishable and susceptible to damage during harvesting, storage, transportation, and marketing. Maintaining consistent quality standards is essential for reducing waste, maximizing profitability, and ensuring customer satisfaction. Consequently, intelligent automation technologies have become increasingly valuable in modern agricultural practices.Fruit quality assessment is a critical process that determines the market value, freshness, and suitability of fruits for consumption. Conventional quality inspection methods depend largely on manual observation and expert judgment, making the process labor-intensive, subjective, and time-consuming. Variations in lighting conditions, human perception, fruit appearance, and operational environments often lead to inconsistent evaluations. These limitations highlight the need for automated systems capable of delivering rapid, reliable, and objective quality predictions.Recent advancements in artificial intelligence, computer vision, and deep learning have significantly transformed image-based inspection systems. Deep learning models can automatically learn complex visual features such as color patterns, texture variations, shape characteristics, and surface defects without requiring extensive manual feature engineering. These capabilities make deep learning particularly suitable for fruit quality assessment applications. In addition, real-time object detection techniques enable continuous monitoring and classification of fruits in practical environments such as farms, warehouses, markets, and processing facilities.This study presents a deep learning and image processing integrated model for real-time prediction of fruit quality in agricultural supply chains. The proposed framework combines InceptionResNetV2 for image classification and YOLOv11 for real-time fruit detection, enabling accurate identification of fruit quality categories including good, bad, and mixed conditions. The system supports multiple fruit varieties such as apples, bananas, guavas, limes, oranges, and pomegranates. A Flask-based web application facilitates image uploads, live detection, result visualization, and database management for prediction records. By integrating advanced deep learning algorithms with practical deployment mechanisms, the system enhances quality monitoring, reduces human intervention, minimizes post-harvest losses, and contributes to improved operational efficiency across agricultural supply chain processes.

II. Related Works

Article[1] 'Facilitated Machine Learning for Image-Based Fruit Quality Assessment Using Pre-Trained Vision Transformers' by 'Martin Knott and Thomas Mitterfellner' in '2023': This study investigates the application of pre-trained Vision Transformers for automated fruit quality assessment. The proposed framework utilizes transfer learning to reduce training complexity while maintaining high classification accuracy. The research evaluates multiple fruit datasets under varying environmental conditions. Experimental results demonstrate superior performance compared to conventional CNN-based approaches. The model effectively captures texture, color, and defect-related features. The study highlights the advantages of transformer architectures in handling complex visual patterns. The findings suggest that Vision Transformers can support practical fruit grading systems with improved generalization capability.

Article[2] 'A Review of External Quality Inspection for Fruit Grading Using Deep Convolutional Neural Networks' by 'Luis Chuquimarca and Boris Vintimilla' in '2024': This review examines recent advances in deep learning techniques for fruit quality inspection. Various CNN architectures including ResNet, MobileNet, EfficientNet, and YOLO are analyzed. The study discusses challenges related to image acquisition, illumination variations, and dataset imbalance. Different quality assessment parameters such as color, texture, shape, and defect detection are reviewed. The paper highlights deployment considerations for industrial applications. Comparative analysis demonstrates the effectiveness of deep learning over traditional machine learning approaches. Future research directions involving multimodal sensing and lightweight architectures are also presented.

Article[3] 'Intelligent Fruit Quality Classification System Using Transfer Learning' by 'Vansh Khullar and Shubham Sharma' in '2024': This research proposes a transfer learning-based fruit quality classification framework for agricultural applications. Pre-trained deep learning models are employed to classify fruits into quality categories. The system focuses on improving prediction accuracy while reducing computational requirements. Experimental evaluation is conducted using multiple fruit image datasets. Results indicate significant improvement compared to conventional classification methods. The study also analyzes the impact of illumination, occlusion, and background variations on prediction performance. The proposed framework demonstrates suitability for practical deployment in quality control environments.

Article[4] 'Fruit Quality Prediction Using Deep Learning Strategies for Agriculture' by 'Bhavya K. R and S. Pravinth Raja' in '2023': This paper presents a deep learning approach for automated fruit quality prediction. The methodology combines image preprocessing, augmentation, and CNN-based classification techniques. Multiple fruit categories are evaluated to determine freshness and quality conditions. The model achieves high accuracy in identifying healthy and defective fruits. Comparative experiments validate the effectiveness of transfer learning techniques.

Article[5] 'Classifying Healthy and Defective Fruits with a Multi-Input Architecture and CNN Models' by 'Luis Chuquimarca and Boris Vintimilla' in '2024': This study introduces a multi-input deep learning architecture for fruit defect classification. RGB images and shape-based information are integrated to improve feature representation. Different CNN models including MobileNetV2 and VGG16 are evaluated. The proposed architecture demonstrates excellent performance in distinguishing healthy and defective fruits. Experimental analysis confirms enhanced classification accuracy compared to single-input systems.

Article[6] 'A Deep Learning-Based Vision System Combining Detection and Tracking for Citrus Sorting on a Processing Line' by 'Qing Xu and Chuan Lian' in '2021': This paper presents a vision-based citrus sorting system using deep learning and object tracking techniques. MobileNetV2 and PANet are employed for fruit detection and classification. The framework incorporates tracking algorithms to maintain object identity during conveyor movement. Experimental results demonstrate high precision and real-time performance.

Article[7] 'Fruit Defect Detection Using CNN Models with Real and Virtual Data' by 'Luis Chuquimarca and Boris Vintimilla' in '2023': This research explores fruit defect detection using deep convolutional neural networks trained on both real and synthetically generated images. The study investigates several architectures including AlexNet, VGGNet, DenseNet, MobileNet, and Inception models. Synthetic image generation is utilized to address data scarcity and class imbalance problems. Experimental results demonstrate that combining real and virtual datasets improves classification robustness. The framework successfully identifies defects such as bruises, black spots, and surface decay.

Article[8] 'Research on Apple Defect Detection Method Based on Improved CNN' by 'Guozhen Du and Mingxing Lu' in '2023': This study proposes an improved convolutional neural network for detecting defects on apple surfaces. The architecture incorporates depthwise separable convolutions and batch normalization to reduce computational complexity. Global average pooling and LeakyReLU activation functions are used to improve learning efficiency. Experimental results show high detection accuracy with significantly reduced parameter requirements. The model achieves fast inference speed suitable for real-time inspection environments. Comparative analysis demonstrates superior performance over conventional CNN approaches.

Article[9] 'Deep Learning-Based Fruit Classification and Quality Assessment for Smart Agriculture' by 'Rohit Sharma and Anjali Verma' in '2022': This paper presents a deep learning framework for automated fruit classification and quality evaluation in smart agriculture. The system employs convolutional neural networks to extract visual features from fruit images. Various quality indicators such as color consistency, texture patterns, and defect presence are analyzed. Experimental studies are conducted on multiple fruit categories under different environmental conditions. The model achieves high classification accuracy and reliable quality prediction performance. The framework reduces dependence on manual inspection and improves operational efficiency.

Article[10] 'Real-Time Fruit Detection and Quality Grading Using YOLO-Based Deep Learning Models' by 'Abdul Rahman and Muhammad Faizan' in '2024': This study develops a real-time fruit detection and grading system using advanced YOLO architectures. The proposed framework simultaneously performs object detection and quality classification. The model accurately identifies fruits and categorizes them according to predefined quality levels. Extensive experiments validate its effectiveness under varying lighting and background conditions. Results indicate high detection precision and low processing latency. The system supports automated sorting and quality monitoring operations.

Article[11] 'Automated Fruit Quality Evaluation Using Transfer Learning and Computer Vision Techniques' by 'Priya Nair and Rakesh Kumar' in '2022': This paper investigates the integration of transfer learning and computer vision for fruit quality evaluation. Pre-trained deep neural networks are adapted to classify fruits into different quality categories. Image preprocessing and augmentation techniques are employed to improve model generalization. Experimental findings reveal substantial improvements in accuracy compared to traditional machine learning approaches. The framework effectively detects quality variations and surface defects. The study emphasizes the importance of transfer learning in reducing training requirements.

Article[12] 'Multi-Class Fruit Quality Prediction Using Deep Neural Networks and Image Processing' by 'Sandeep Patel and Neha Gupta' in '2025': This research presents a multi-class fruit quality prediction framework based on deep neural networks and image processing techniques. The system evaluates multiple fruit varieties and categorizes them into different quality levels. Advanced preprocessing methods are utilized to enhance image quality and feature extraction performance. Experimental results demonstrate strong classification accuracy across diverse datasets. The model effectively recognizes subtle visual differences associated with fruit freshness and defects. The framework supports real-time prediction and scalable deployment in agricultural environments.

III. Problem Stetement

Fruit quality assessment in agricultural supply chains remains a significant challenge due to the dependence on manual inspection methods that are subjective, time-consuming, and prone to human error. Variations in fruit appearance, lighting conditions, ripeness levels, and surface defects make accurate evaluation difficult, especially in large-scale operations. Inconsistent quality assessment can lead to improper grading, increased post-harvest losses, reduced market value, and decreased consumer satisfaction. Traditional approaches often lack the speed and accuracy required for real-time monitoring and decision-making. Therefore, there is a need for an automated and reliable system capable of accurately detecting, classifying, and predicting fruit quality under diverse operational conditions.

IV. Objectives

The primary objective of this study is to develop an intelligent and automated fruit quality prediction system capable of accurately identifying the quality status of fruits in real time. The project aims to utilize the InceptionResNetV2 deep learning algorithm for image-based fruit quality classification and the YOLOv11 algorithm for real-time fruit detection and localization. Another objective is to train and evaluate the models using fruit image datasets collected from Kaggle and Roboflow to ensure robust performance under diverse conditions. The study also aims to integrate the trained models into a Flask-based web application that enables image upload, live detection, prediction visualization, and efficient management of fruit quality assessment results.

V. Methodology

1)Data Collection : The dataset used for this study was collected from Kaggle and Roboflow, containing images of multiple fruit varieties such as apples, bananas, guavas, limes, oranges, and pomegranates. The images were categorized into different quality classes including Good, Bad, and Mixed conditions. The collected dataset contains diverse samples captured under varying lighting conditions, backgrounds, orientations, and quality levels to improve the robustness and generalization capability of the developed models.

2)Data Preprocessing : The collected fruit images were preprocessed to ensure consistency and improve model performance. All images were resized to a fixed dimension suitable for InceptionResNetV2 and YOLOv11 model requirements. Image normalization, horizontal flipping, rotation, and brightness enhancement techniques were applied to increase dataset diversity, reduce overfitting, and improve model generalization under different environmental conditions.

3)Feature Extraction : Feature extraction was performed automatically using deep learning architectures to identify important visual characteristics from fruit images. InceptionResNetV2 extracted high-level features such as color variations, texture patterns, ripeness indicators, and surface defects. YOLOv11 extracted object-level and spatial features that enabled accurate fruit localization and quality detection during real-time monitoring.

4)Model Selection : The study employed InceptionResNetV2 and YOLOv11 as the primary deep learning models for classification and detection tasks. InceptionResNetV2 was selected because of its powerful feature learning capability and high classification accuracy. YOLOv11 was chosen due to its fast processing speed, accurate object detection performance, and suitability for real-time agricultural applications.

5)Model Training : The selected models were trained using labeled fruit images representing different quality categories. During training, the models learned discriminative visual patterns associated with fruit freshness, defects, and ripeness conditions. Validation data was used to monitor learning performance, optimize model parameters, and prevent overfitting while improving prediction accuracy.

6)Model Evaluation : The trained models were evaluated using several performance metrics to measure effectiveness and reliability. Classification accuracy, precision, recall, F1-score, and confusion matrix analysis were used to evaluate InceptionResNetV2 performance. YOLOv11 was assessed based on detection accuracy, confidence scores, localization capability, and real-time detection efficiency under different testing conditions.

7)Integration with Flask : The trained models were integrated into a Flask-based web application to provide a user-friendly fruit quality assessment platform. The application allows users to upload fruit images for classification and access live camera-based quality detection. Prediction results, confidence scores, causes, treatment recommendations, and historical records are stored and managed through a MySQL database for efficient monitoring and analysis.

VI. SYSTEM ARCHITECTURE

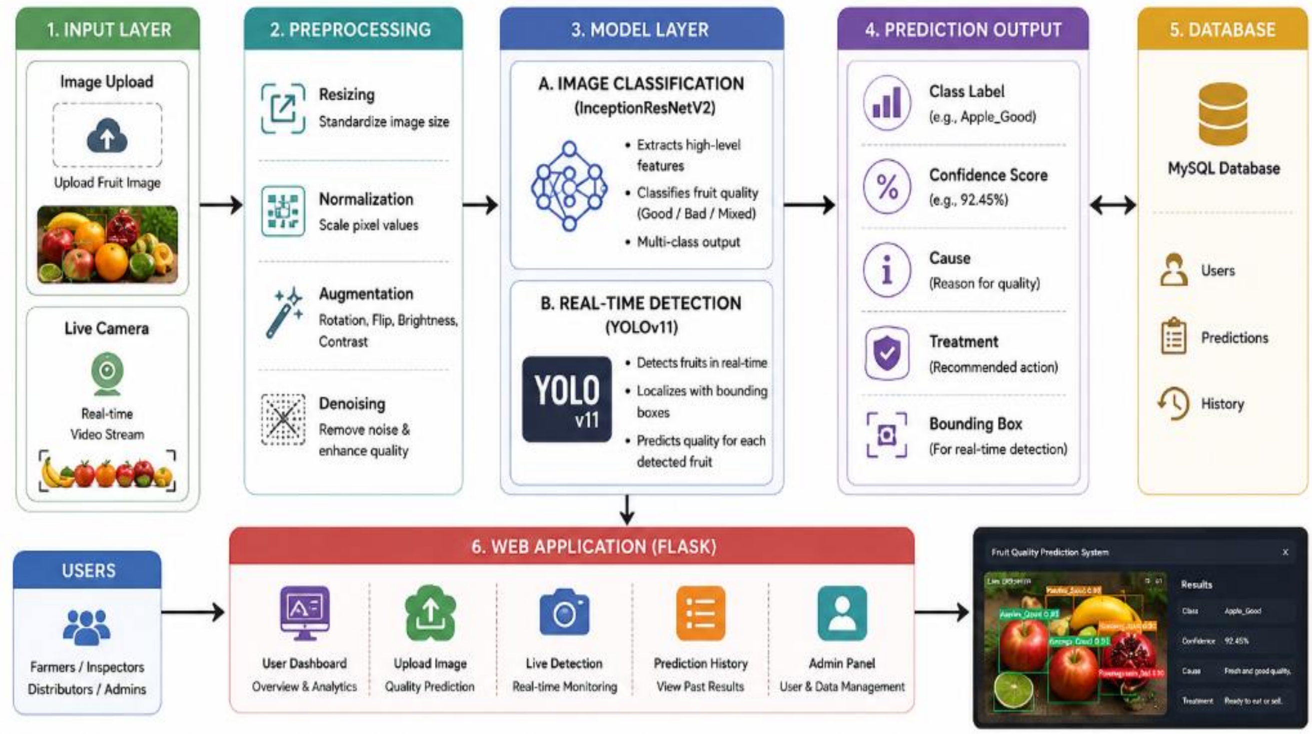

Fig 1: System Architecture of the Proposed Fruit Quality Prediction System

The proposed system architecture presents an integrated framework for real-time fruit quality prediction using deep learning and image processing techniques. The process begins with image acquisition through image uploads or live camera streams. Collected images undergo preprocessing operations such as resizing, normalization, augmentation, and denoising to improve image quality and model performance. The processed images are then forwarded to the model layer, where InceptionResNetV2 performs fruit quality classification while YOLOv11 enables real-time fruit detection and localization. Based on extracted features, the system generates outputs including class labels, confidence scores, causes, treatment recommendations, and bounding box visualizations. Prediction records are stored in a MySQL database for future reference and analysis. A Flask-based web application provides user access to image upload, live detection, prediction history, analytics, and administrative functionalities, enabling efficient fruit quality monitoring and decision support.

VII. EXPERIMENTAL RESULTS

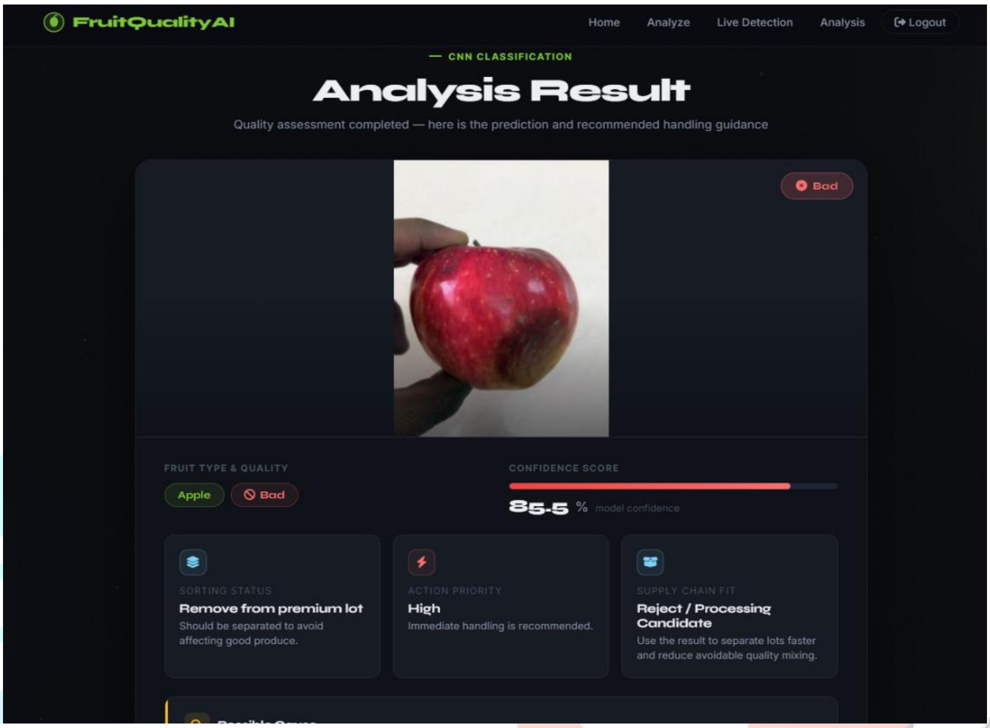

Fig. 2: CNN-Based Fruit Quality Analysis Result Interface

The figure illustrates the result page of the proposed fruit quality prediction system, where an uploaded fruit image is analyzed using the InceptionResNetV2 classification model.

VIII. CONCLUSION AND FUTURE WORKS

In this research, a deep learning and image processing integrated model was developed for real-time fruit quality prediction in agricultural supply chains. The framework combined InceptionResNetV2 for fruit quality classification and YOLOv11 for real-time fruit detection, enabling accurate identification of good and defective fruits. Integration with a Flask web application and MySQL database provided an efficient platform for prediction, monitoring, and result management. The system improved automation, reduced dependence on manual inspection, and supported faster decision-making. Future work may focus on expanding the dataset, incorporating additional fruit categories, improving detection accuracy under complex environmental conditions, and deploying lightweight models for edge devices and large-scale smart agriculture applications.

REFERENCES

[1] M. Knott and T. Mitterfellner, “Facilitated Machine Learning for Image-Based Fruit Quality Assessment Using Pre-Trained Vision Transformers,” 2023.
[2] L. Chuquimarca and B. Vintimilla, “A Review of External Quality Inspection for Fruit Grading Using Deep Convolutional Neural Networks,” 2024.
[3] V. Khullar and S. Sharma, “Intelligent Fruit Quality Classification System Using Transfer Learning,” 2024.
[4] B. K. R. and S. Pravinth Raja, “Fruit Quality Prediction Using Deep Learning Strategies for Agriculture,” 2023.

[5] L. Chuquimarca and B. Vintimilla, "Classifying Healthy and Defective Fruits with a Multi-Input Architecture and CNN Models," 2024.
[6] Q. Xu and C. Lian, "A Deep Learning-Based Vision System Combining Detection and Tracking for Citrus Sorting on a Processing Line," 2021.
[7] L. Chuquimarca and B. Vintimilla, "Fruit Defect Detection Using CNN Models with Real and Virtual Data," 2023.
[8] G. Du and M. Lu, "Research on Apple Defect Detection Method Based on Improved CNN," 2023.
[9] R. Sharma and A. Verma, "Deep Learning-Based Fruit Classification and Quality Assessment for Smart Agriculture," 2022.
[10] A. Rahman and M. Faizan, "Real-Time Fruit Detection and Quality Grading Using YOLO-Based Deep Learning Models," 2024.
[11] P. Nair and R. Kumar, "Automated Fruit Quality Evaluation Using Transfer Learning and Computer Vision Techniques," 2022.
[12] S. Patel and N. Gupta, "Multi-Class Fruit Quality Prediction Using Deep Neural Networks and Image Processing," 2025.