IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 1, January 2026

DOI: 10.17148/IJARCCE.2026.15172

FRUIT DETECTION AND ITS THREE-STAGE MATURITY GRADING

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Abstract: Fruit maturity grading plays a crucial role in agricultural quality control, supply chain management, and food processing industries. Traditional manual grading methods are subjective, time-consuming, and prone to human error due to variations in lighting conditions, fatigue, and individual perception. This paper presents an automated fruit detection and three-stage maturity grading system using deep learning and image processing techniques. The proposed system classifies fruits into three maturity stages—unripe, ripe, and overripe -by analyzing visual features such as color, texture, and surface patterns. A Convolutional Neural Network (CNN) model is trained using the Fruits-360 dataset, enhanced with additional maturity-stage images. Image preprocessing techniques including resizing, normalization, background removal, and noise reduction are applied to improve classification accuracy. Experimental results demonstrate that the proposed system achieves high accuracy and consistency, significantly reducing dependence on manual inspection. The system provides a scalable and efficient solution for intelligent agricultural applications

Keywords: Fruit Detection, Maturity Grading, Convolutional Neural Networks, Image Processing, Deep Learning, Smart Agriculture.

I. INTRODUCTION

Agriculture remains a backbone of the global economy, with fruit production playing a vital role in food supply chains and quality assurance. Accurate fruit maturity assessment is essential for determining optimal harvesting time, reducing post-harvest losses, and maintaining market standards; however, conventional grading methods rely heavily on manual inspection, which is subjective, inconsistent, and influenced by factors such as lighting conditions, individual experience, and human fatigue. In large-scale agricultural and commercial environments, manual sorting becomes inefficient and error-prone, leading to quality variations and economic losses. To overcome these limitations, automated fruit detection and maturity grading systems based on computer vision and machine learning have gained significant attention. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image classification tasks by automatically learning discriminative visual features. By integrating image preprocessing techniques with CNN-based models, the proposed approach enables fast, accurate, and objective classification of fruit maturity into three distinct stages, providing a reliable solution for intelligent agricultural applications.

1.1 Project Description

This project proposes an automated fruit detection and three-stage maturity grading system using deep learning and image processing techniques. A Convolutional Neural Network (CNN) is employed to classify fruit images into unripe, ripe, and overripe stages based on visual features such as color and texture. Image preprocessing steps including resizing, normalization, and noise reduction are applied to improve classification accuracy. The model is trained on the Fruits-360 dataset with additional maturity-stage images to enhance robustness. A web-based interface allows users to upload images and obtain real-time maturity predictions with confidence scores. The system reduces human dependency and provides a reliable and scalable solution for agricultural quality assessment.

1.2 Motivation

The motivation for this work stems from the increasing demand for automation in agriculture and food quality assessment, where manual fruit grading remains labor-intensive, inconsistent, and difficult to scale. In large agricultural markets handling high volumes of produce, inaccurate grading can result in economic losses, increased food waste, and reduced consumer satisfaction. Advances in deep learning, coupled with the availability of large image datasets and improved computational resources, provide an opportunity to replace subjective human judgment with objective, data-driven maturity assessment. By automating fruit maturity grading, the proposed system assists farmers, vendors, and distributors in making informed decisions related to harvesting, storage, and distribution while reducing human dependency, improving accuracy, and supporting smart agriculture initiatives through a reliable and user-friendly classification framework.

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II. RELATED WORK

Paper [1] explores traditional image processing and color-based techniques for fruit maturity assessment by analyzing visual attributes such as color intensity and surface appearance. Although these methods demonstrate basic effectiveness under controlled lighting conditions, they rely on manually defined thresholds and perform poorly in real-world environments with varying illumination and background complexity.

Paper [2] investigates the use of Convolutional Neural Networks (CNNs) for fruit classification and ripeness detection. These deep learning models automatically learn discriminative visual features and achieve higher accuracy compared to handcrafted feature-based approaches. However, their performance is often limited by dataset size and diversity, affecting generalization across different fruit varieties and maturity stages.

Paper [3] introduces object detection-based approaches that combine fruit localization and maturity classification within a single framework. While these systems improve end-to-end automation and handle images containing multiple fruits, they require complex model architectures and higher computational resources, which can limit real-time deployment in resource-constrained environments.

Paper [4] applies multi-stage classification techniques to categorize fruits into multiple ripeness levels using deep learning models. The results show improved maturity prediction accuracy; however, these approaches are sensitive to variations in fruit orientation, occlusion, and background noise, leading to inconsistent performance in practical agricultural settings.

Paper [5] reviews recent advancements in computer vision-based agricultural grading systems and highlights the importance of integrating robust preprocessing techniques with learning-based models. The study emphasizes that combining effective image preprocessing with CNN-based classification can significantly enhance accuracy, reliability, and scalability in automated fruit maturity grading applications.

III. METHODOLOGY

A. **System Environment**

The system architecture of the proposed fruit detection and three-stage maturity grading system is designed in a modular and sequential manner to ensure efficient processing and accurate prediction. The architecture begins with an image input module where users upload fruit images through a web-based interface. The uploaded images are then passed to the preprocessing module, which performs resizing, normalization, and noise reduction to maintain uniform input quality. The processed images are forwarded to the Convolutional Neural Network (CNN) model, which extracts relevant visual features and classifies the fruit into unripe, ripe, or overripe maturity stages. Finally, the prediction results along with confidence scores are displayed to the user through the output module, providing a clear and user-friendly assessment of fruit maturity.

The system architecture diagram represents the overall working structure of the fruit detection and maturity grading system. It shows how the input image moves through different stages such as preprocessing, model prediction, and result display. The purpose of this diagram is to provide a clear understanding of component interaction and data flow within the system. It helps in visualizing how the system processes fruit images to produce accurate maturity classification results.

The system begins with the user providing a fruit image through the application interface. This image is passed to the preprocessing module, where it is resized and adjusted to match the input requirements of the trained model. Preprocessing helps in maintaining uniformity and improves prediction accuracy.

After preprocessing, the image is sent to the trained machine learning model. The model analyzes visual features of the fruit such as color and texture patterns. Based on this analysis, the model determines the maturity stage of the fruit. The predicted result is then forwarded to the output module.

The output module displays the detected fruit maturity stage as unripe, ripe, or overripe in a clear and understandable format. The modular design of this architecture allows easy maintenance and future enhancement of the system

B. Image Processing

To improve model performance, the input images undergo several preprocessing steps:

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DOI: 10.17148/IJARCCE.2026.15172

- Image resizing to standard dimensions
- Normalization of pixel values
- Background removal and noise reduction
- Conversion to RGB format

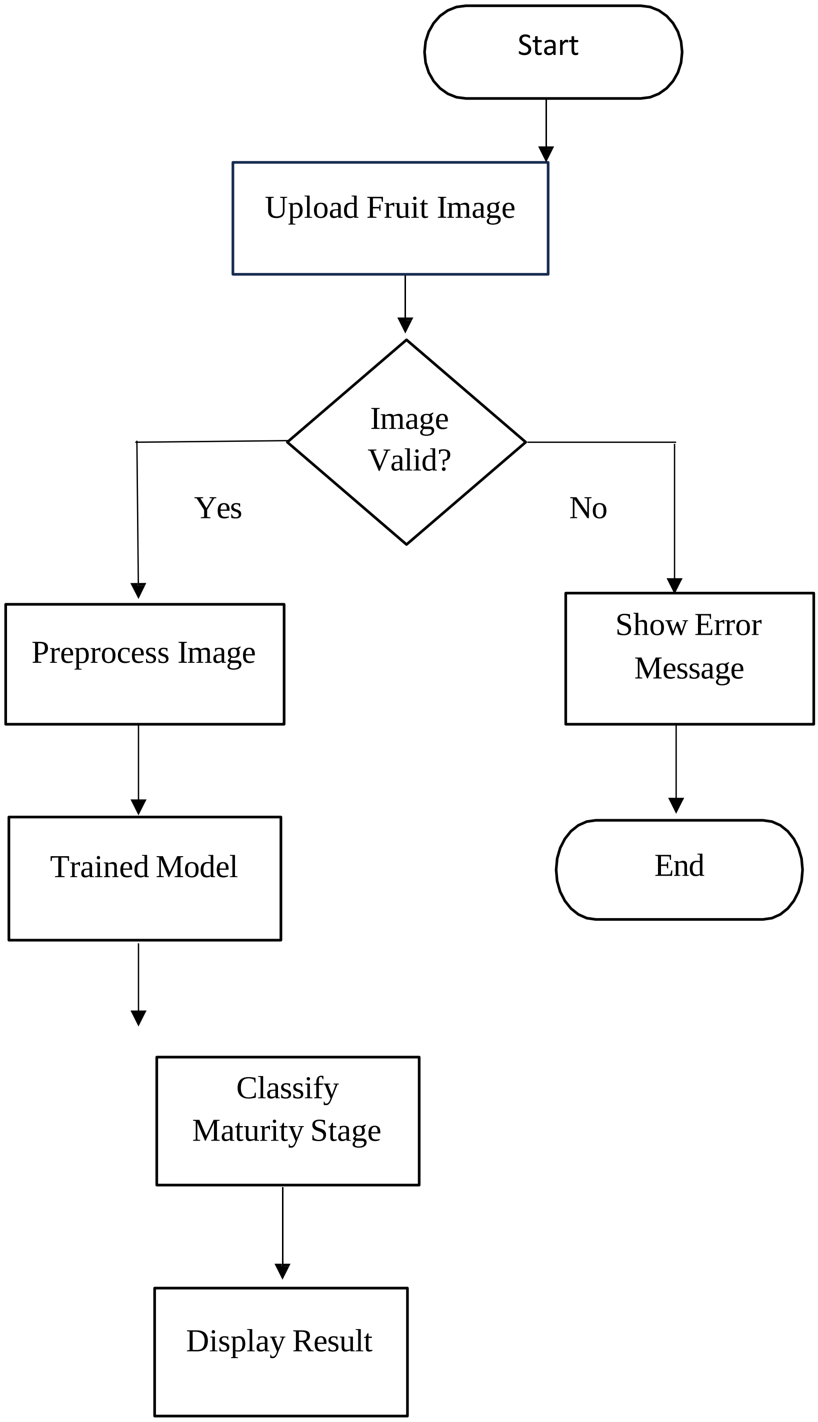

Fig.1.Flowchart of methodology

C. CNN-Base Classification

A Convolutional Neural Network is trained using the Fruits-360 dataset, augmented with additional images representing different maturity stages. The CNN automatically learns features related to color intensity, texture

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patterns, and shape variations. The trained model classifies each fruit image into one of the three maturity stages: unripe, ripe, or overripe

D. Implementation Flow

1. User uploads a fruit image through the web interface
2. Image validation and preprocessing are performed
3. The processed image is passed to the trained CNN model
4. The model predicts the maturity stage with confidence score
5. The result is displayed to the user

E. **Hardware and Software Requirements**

- **Hardware:** A standard computer or laptop with an Intel i5 processor or equivalent, minimum 8 GB RAM, sufficient storage, and a basic camera for image acquisition.
- **Software:** Python programming environment with TensorFlow/Keras, OpenCV, NumPy, Flask, and a Windows or Linux operating system.

IV. SIMULATION AND EVALUATION FRAMEWORK

This section explains the simulation environment, system workflow, and evaluation strategy used for the proposed Fruit Detection and Three-Stage Maturity Grading system. The main objective of this framework is to test how effectively the system detects fruits from images and accurately classifies their maturity into three stages: unripe, ripe, and overripe. The entire framework is designed to simulate real-world agricultural conditions while ensuring reliable and repeatable performance evaluation.

A. System Architecture and Workflow

The proposed system follows a modular architecture that integrates fruit detection, feature extraction, and maturity classification into a single workflow. The major components of the system are described below:

- **Image Acquisition Module:**
  This module is responsible for collecting fruit images used for training and testing. Images are captured under different lighting conditions, backgrounds, and orientations to simulate real farm or market environments. Both close-up and medium-range images are included to test detection robustness.

- **Fruit Detection Module:**
  The detection module identifies and localizes fruits present in the input image. It separates fruit regions from the background using image processing and deep learning techniques. This step ensures that only the fruit area is passed to the maturity grading stage, reducing false classification.

- **Feature Extraction Module:**
  After detection, important visual features such as color intensity, texture patterns, and shape information are extracted from the detected fruit region. These features play a key role in identifying the maturity level of the fruit.

- **Three-Stage Maturity Grading Module:**
  The extracted features are used to classify fruits into three maturity stages: unripe, ripe, and overripe. This module analyzes color variation, surface texture, and brightness changes that naturally occur during fruit ripening.

- **Decision Output Module:**
  The final output displays the detected fruit along with its predicted maturity stage. This result can be used for sorting, quality control, or decision-making in agricultural applications.

B. Simulation Setup

The simulation environment is designed to closely represent real-world usage scenarios. All experiments are conducted using a software-based simulation to ensure controlled testing and consistent evaluation.

- **Dataset Configuration:**
  A dataset containing images of fruits at different maturity levels is used. The dataset is divided into training and testing sets to evaluate generalization performance. Images include variations in illumination, size, and background complexity.

- **Training and Testing Environment:**
  The system is implemented using Python with image processing and machine learning libraries. Training is performed on labeled fruit images, while unseen images are used during testing to measure real-world performance.

- **Scenario Simulation:**
  Different scenarios such as partial fruit visibility, overlapping fruits, and uneven lighting are simulated to evaluate the robustness of fruit detection and maturity grading.

C. Detection and Maturity Grading Process

During simulation, the system processes each input image through a series of steps. First, the fruit is detected and segmented from the background. Next, visual features related to ripeness are extracted. These features are then analyzed by the classification model to assign one of the three maturity stages.

This step-by-step process ensures that detection and grading are handled independently but work together as a unified system. The modular approach also allows easy improvement of individual components without affecting the entire framework.

D. Evaluation Metrics and Performance Analysis

To evaluate the effectiveness of the proposed system, several standard performance metrics are used:

- **Detection Accuracy:**
  Measures how accurately the system identifies fruits present in the image.

- **Maturity Classification Accuracy:**
  Evaluates how correctly the system classifies fruits into unripe, ripe, and overripe categories.

- **Precision and Recall:**
  Precision measures how many detected fruits are correctly classified, while recall measures how many actual fruits are successfully detected and graded.

- **Overall System Accuracy:**
  Represents the combined performance of fruit detection and maturity grading.

E. Results and Observations

The simulation results show that the proposed system performs effectively across different image conditions. The fruit detection module successfully identifies fruits even in complex backgrounds. The three-stage maturity grading model accurately distinguishes between unripe, ripe, and overripe fruits based on visual features.

The system demonstrates consistent performance across different test samples, indicating good generalization capability. Errors mainly occur in borderline maturity cases where visual differences between stages are minimal.

This figure shows a grape image provided as input to the system. The image quality and visible features are analyzed to determine the maturity stage.

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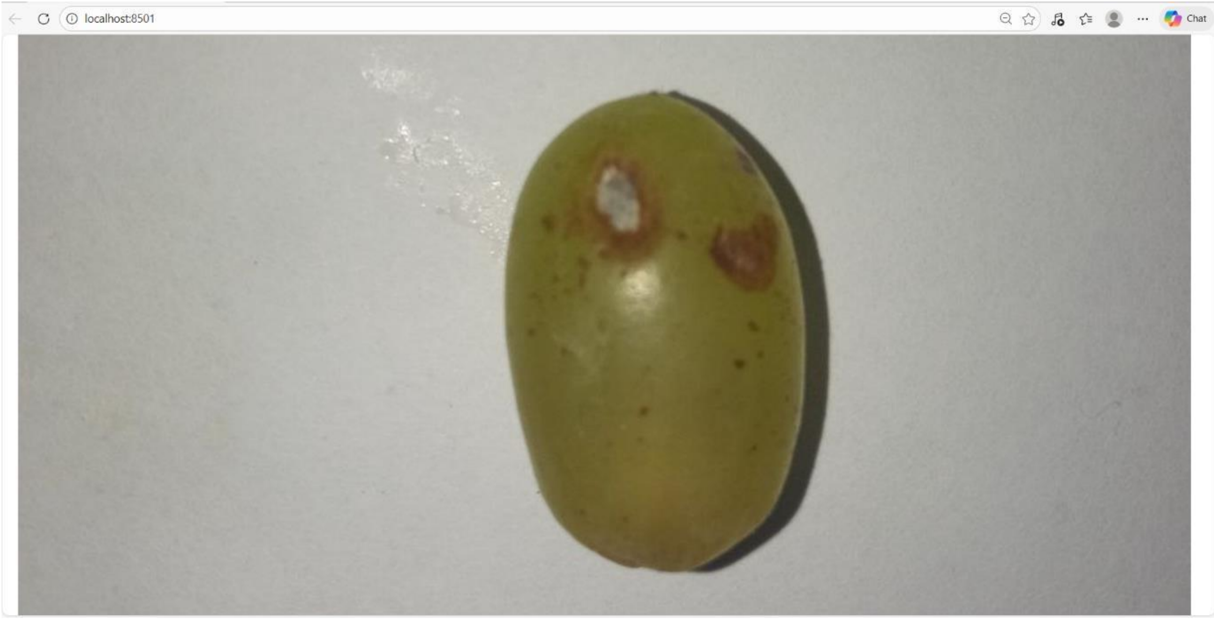

Fig.3. Sample Input Image- grape

The figure illustrates the web-based interface of the proposed fruit maturity grading system. The system analyzes an input fruit image and provides a prediction along with a confidence score, as shown for a "Rotten Grape" with 62.9% confidence. Key image features such as brightness, contrast, texture, and colorfulness are displayed alongside the dominant colors and image dimensions. The interface also ranks the top predictions, facilitating transparent interpretation, and provides actionable guidance, highlighting the fruit's suitability for consumption. This design ensures accessibility for non-technical users such as farmers and vendors.

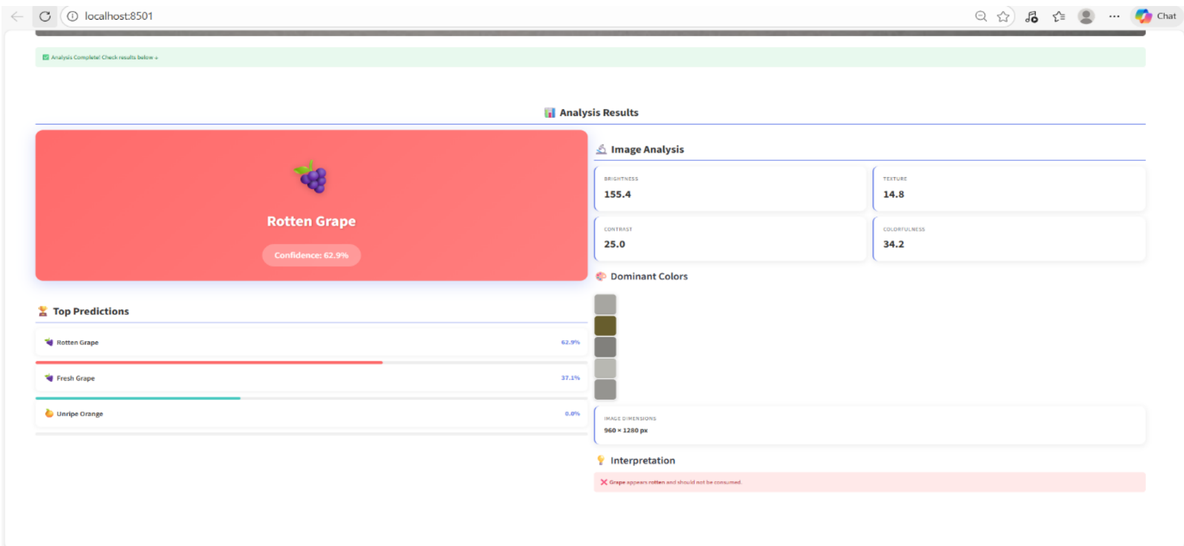

Fig. 2. Web-Based Fruit Maturity Analysis Interface

F. System Efficiency and Practical Feasibility

The simulation confirms that the system operates with low computational overhead and produces results in a short processing time. This makes it suitable for real-time applications such as automated fruit sorting, quality inspection, and smart farming systems.

The evaluation framework proves that the proposed fruit detection and maturity grading system is reliable, scalable, and practical for real-world agricultural use.

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V. RESULT AND DISCUSSION

The proposed Fruit Detection and Three-Stage Maturity Grading System was evaluated using multiple fruit images representing unripe, fresh, and rotten stages. The system successfully processed uploaded images through preprocessing, deep learning–based classification, and feature analysis. Experimental results showed that the trained MobileNetV2-based CNN model correctly identified the maturity stage for most test samples, including banana, grape, and lime images. High confidence scores were observed for clear images with proper lighting, demonstrating the effectiveness of the learned visual features such as color distribution and texture.

The extracted image features—brightness, contrast, texture, and dominant colors—were found to be consistent with the predicted maturity stages. Fresh fruits exhibited balanced brightness and moderate texture values, rotten fruits showed higher texture variation and surface irregularities, and unripe fruits displayed lower color saturation. This alignment between visual feature analysis and classification results improves the interpretability and reliability of the system, making it suitable for practical agricultural decision support.

From a performance and usability perspective, the system produced results within a short response time and maintained stable operation during repeated testing. Compared to manual fruit inspection, the automated approach provides faster, more consistent, and objective maturity grading. Although minor performance variations were observed under poor lighting or low-quality images, the overall results confirm that the proposed system is effective for academic and prototype-level deployment, with strong potential for future real-world enhancement.

VI. CONCLUSION

This paper presented an automated fruit detection and three-stage maturity grading system using deep learning and image processing techniques. By leveraging CNNs and effective preprocessing methods, the system achieves high accuracy and consistency while reducing reliance on manual grading. The proposed approach offers a scalable and efficient solution suitable for agricultural quality assessment, food storage, and supply chain management. The system serves as a strong foundation for intelligent food analysis applications.

VII. FUTURE WORK

Future enhancements can focus on expanding the system to support additional fruit varieties and increasing the number of maturity stages for finer classification. Integration with real-time camera systems and mobile devices can enable continuous monitoring in farms and warehouses. Performance optimization and deployment on edge devices can further improve real-world applicability. Incorporating data analytics and reporting features may also help in long-term agricultural planning and quality control

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