

**Software Engineering Department**

**Braude College of Engineering**

**Real time fruit grading using data mining and machine learning**

**Project code: 25-2-D-6**

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**Git repository link:** <https://github.com/Drorh473/fruit_grading.git>

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# Abstract

The labor-intensive nature of manual fruit grading in agricultural supply chains creates significant challenges for small-scale producers. This project introduces an innovative real-time visual inspection system that combines multi-view camera inputs with state-of-the-art deep learning models to automate fruit quality assessment. Our solution incorporates a custom-designed conveyor belt system featuring a specialized inspection box equipped with strategically positioned cameras and LED strip lighting for optimal image capture. Our approach integrates lightweight convolutional neural network (CNN) architectures to process temporal sequences of fruit images, detecting defects and classifying ripeness levels across various fruit types. The system efficiently segments multiple fruit instances from images using advanced computer vision techniques and applies sophisticated image enhancement to ensure consistent performance across varying lighting conditions.

Key words: Computer vision, Deep learning, CNN, Fruit classification, Image processing, Quality control.

# 1 Introduction

With increased consumer demand for high-quality fruits across global markets, there arises a critical need for advanced automated fruit grading systems. Traditional manual inspection approaches have demonstrated significant limitations in accuracy, consistency, and efficiency due to the labor-intensive nature of visual inspection and human-induced variability [1]. The agricultural industry faces persistent challenges in fruit classification, grading, and quality assessment processes while attempting to meet the growing demand for consistently high-quality fresh produce in global markets.

The relevance of such technology is particularly pronounced given the agricultural labor shortages reported across major producing regions, the labor is the U.S. agricultural sector’s third largest production expense [2].

This labor scarcity has led to increased operational costs, with wage inflation for agricultural quality inspectors outpacing general agricultural wages by 15-20% according to Rotz et al. [3]. Furthermore, Zhao and Li [4] demonstrate that smaller farming operations with fewer than ten employees experience disproportionate challenges in maintaining consistent quality standards, as these operations cannot dedicate specialized personnel exclusively to grading tasks.

As noted by Ismail and Malik, "traditional manual visual grading of fruits has been one of the important challenges faced by the agricultural industry due to its laborious nature as well as inconsistency in inspection and classification process" [5]. This inconsistency becomes more pronounced when operations must rely on less-experienced seasonal workers during harvest periods, with error rates increasing by up to 23% during peak season according to longitudinal studies by Weinberger and Lumpkin [6].

Our proposed solution directly addresses these challenges by implementing an end-to-end automated inspection system that combines advanced computer vision techniques with efficient deep learning models through a comprehensive pipeline: image acquisition via a specialized mechanical conveyor system developed with a mechanical engineering student; feature extraction using ShuffleNetV2, a lightweight CNN with ReLU activation functions that balances computational efficiency with classification accuracy through innovative channel shuffle operations [7]; temporal processing with time-distributed feature flattening and pooling for multi-view assessment; integration of feature vectors from multiple cameras when applicable; and final classification through fully connected layers with softmax activation function to generate probability distributions across quality classes. This integrated hardware-software approach ensures high-accuracy fruit grading capabilities while operating within the processing limitations of embedded systems commonly deployed in agricultural environments, providing consistent, objective quality assessments that exceed traditional manual inspection methods in both accuracy and efficiency.

By reducing dependency on specialized labor for quality control, our system allows agricultural operations to reallocate their limited workforce to tasks that truly require human expertise and judgment, potentially increasing overall production efficiency by 28-35% as projected by similar implementations documented by Gonzalez-Sanchez et al. [8].

# 2 Background and Related Work

**2.1 Fruit Grading in Agriculture**

Fruit grading represents a critical process in the agricultural supply chain, involving the classification of fruits based on various quality parameters such as appearance, size, color, and defects. Traditional manual grading methods are labor-intensive and susceptible to inconsistencies due to human subjectivity and fatigue. As noted by Tripathi and Maktedar [1], these traditional approaches face significant challenges in accuracy, efficiency, and scalability, particularly when dealing with large volumes of produce.

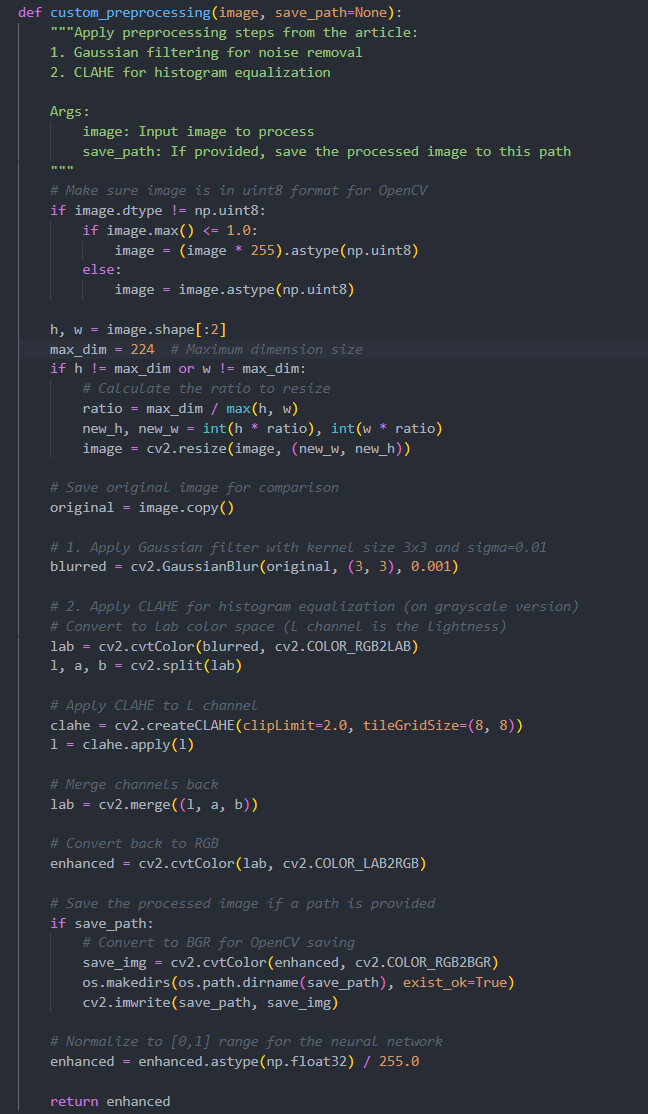
The importance of automated fruit grading systems has grown substantially with increasing global demand for consistent quality standards across agricultural produce. This inconsistency directly impacts product pricing, market acceptance, and consumer satisfaction, underscoring the need for reliable automated systems.

**2.2 Computer Vision for Fruit Quality Assessment**

Computer vision technology has revolutionized fruit quality assessment by providing objective, consistent, and efficient evaluation methods. The application of computer vision in fruit grading typically involves a sequential process:

1. **Image acquisition**: Capturing high-quality images of fruits under controlled lighting conditions
2. **Preprocessing**: Enhancing image quality and reducing noise
3. **Segmentation**: Separating the fruit from the background
4. **Feature extraction**: Identifying relevant features related to quality parameters
5. **Classification**: Categorizing fruits based on extracted features

In our system implementation, we follow a similar workflow with specialized components optimized for real-time processing. Our preprocessing stage employs Gaussian filtering for noise removal and Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement, as demonstrated in our implementation:



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