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# AI Assisted Embedded Vision System for Automatic Fruit Sorting and Grading

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**ABSTRACT:** Fruit grading plays a vital role in the agricultural supply chain by ensuring consistent quality, higher market value, and improved consumer satisfaction. Traditional manual sorting and grading methods are time-consuming, labor-intensive, and highly dependent on human judgment, which often leads to inconsistency and errors in large-scale operations. To overcome these limitations, this project proposes an automatic fruit sorting and grading system that integrates computer vision, ultrasonic sensing, and neural network–based classification techniques. The system acquires real-time images of individual fruits using a camera, from which key visual features such as color, size, shape, and surface defects are extracted through image processing methods. An ultrasonic sensor is employed to estimate the physical dimensions and distance of the fruit, thereby improving the accuracy and consistency of size measurement. The extracted features are then provided as input to a trained neural network model, which classifies the fruits into predefined quality grades. The proposed system minimizes human intervention and ensures uniform, repeatable, and objective fruit quality assessment. Experimental results demonstrate improved classification accuracy and a significant increase in processing speed compared to conventional manual inspection methods. Owing to its scalability, cost-effectiveness, and reliability, the proposed approach is well suited for modern automated agriculture and post-harvest quality management applications.

**Keywords**: AI-Assisted Vision System, Fruit Grading and Sorting, Computer Vision, Neural Network, Ultrasonic Sensor, Image Processing

## 1. Introduction

Agriculture plays a crucial role in the economy of developing countries, where post-harvest quality assessment significantly influences market value and export potential. Fruit grading is an essential step in the agricultural supply chain, as it determines pricing, storage decisions, and consumer acceptance. Traditionally, fruit sorting and grading are performed manually by skilled laborers who evaluate visual characteristics such as color, size, shape, and surface defects. However, manual inspection methods are often subjective, inconsistent, time-consuming, and inefficient for large-scale production environments. With the rapid advancement of automation technologies, computer vision and machine learning techniques have emerged as promising solutions for intelligent agricultural applications. Image processing enables objective evaluation of fruit characteristics by extracting measurable features such as color distribution, geometric properties, and texture patterns. In recent years, neural network–based classification models have demonstrated high accuracy in pattern recognition tasks, making them well suited for automated quality grading systems. In addition to visual inspection, accurate size measurement is an important parameter in fruit grading standards. Conventional camera-based size estimation may suffer from perspective and scaling issues. To address this limitation, ultrasonic sensing technology can be integrated to estimate fruit dimensions and distance measurements, thereby improving grading consistency and reliability. This paper proposes an automatic fruit sorting and grading system that combines computer vision techniques, ultrasonic sensing, and neural network–based classification. The system captures real-time fruit images, extracts relevant visual features, and incorporates ultrasonic measurements to enhance dimensional accuracy. These features are then processed through a trained neural network model to classify fruits into predefined quality grades. The proposed system aims to reduce human intervention, improve grading accuracy, and increase operational efficiency.

## 2. Literature Review

Recent research in automated fruit grading systems has focused on leveraging computer vision, machine learning, and sensor integration to overcome the limitations of manual inspection. Early approaches primarily relied on basic image processing techniques to extract color and size features for classification. For instance, Patil and Kumar employed thresholding and morphological operations to segment fruit images and classify them based on hue and geometric properties [1]. Although effective for controlled environments, these methods suffered from low robustness under variable lighting and background conditions.

To improve classification accuracy, several studies introduced machine learning models such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests. ElMasry et al. developed an SVM-based grading system for apples using color, texture, and shape features extracted from digital images, achieving significant improvement over conventional rule-based classifiers [2]. Similarly, Li and Lu demonstrated enhanced grading performance by integrating texture descriptors such as Local Binary Patterns (LBP) with SVM classification [3]. However, traditional machine learning techniques often require careful feature engineering and are sensitive to noise in the input data. With the advent of deep learning, convolutional neural networks (CNNs) have gained widespread adoption in agricultural image analysis due to their ability to automatically learn discriminative features. Fu et al. proposed a CNN-based mango grading system that achieved superior accuracy compared to handcrafted feature methods [4]. Other researchers have applied transfer learning with pre-trained networks such as AlexNet and VGGNet to accelerate training and improve generalization across different fruit types [5]. Despite these achievements, pure vision-based systems experience challenges in accurately estimating physical dimensions such as size and volume due to depth and perspective limitations. To address this issue, hybrid systems that combine visual and non-visual sensing modalities have been investigated. Chauhan et al. integrated 3D depth sensors with conventional vision techniques to improve size estimation in citrus fruits, showing more consistent measurement results compared to 2D image processing alone [6]. Ultrasonic sensing, known for its cost-effectiveness and simplicity, has been utilized in some agricultural setups for distance measurement and object profiling [7]. However, limited studies have explored the combined use of ultrasonic sensing and neural network classifiers for fruit grading.

In summary, existing literature demonstrates significant progress in automated fruit grading through computer vision and machine learning. While deep learning models enhance classification robustness, the integration of additional sensing modalities has the potential to improve dimension estimation and overall grading accuracy. The proposed system builds upon these advancements by incorporating ultrasonic sensing to complement image-based feature extraction and employing neural network–based classification to achieve fast, reliable, and scalable fruit grading.

## 3. System Architecture and Methodology

The proposed automatic fruit sorting and grading system integrates computer vision, ultrasonic sensing, and neural network–based classification. The overall workflow consists of image acquisition, preprocessing, feature extraction, ultrasonic measurement, feature fusion, and classification. The methodological framework is illustrated in Fig.1 (System Architecture).

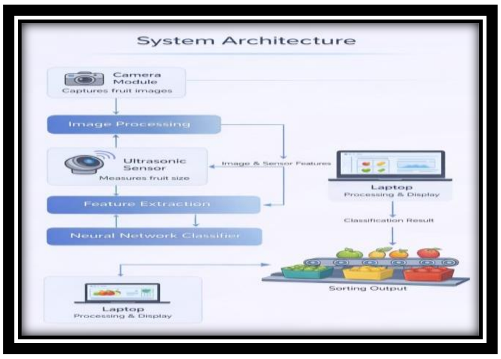


**Figure 1:** *System Architecture*

The Block Diagram of the Proposed System is shown in Fig.2 and the process includes Image Acquisition, Image Preprocessing, Feature Extraction, Ultrasonic Sensor-Based Size Measurement, Feature Fusion, Neural Network-Based Classification and Performance Evaluation.

### 3.1 Image Acquisition

A high-resolution digital camera is used to capture real-time images of individual fruits placed within a controlled background environment. Proper illumination is maintained to minimize shadows and reflections, ensuring consistent image quality. Each fruit image is acquired and stored for further processing.

### 3.2 Image Preprocessing

Preprocessing is performed to enhance image quality and improve segmentation accuracy. The steps include:

- Noise Reduction – Gaussian filtering is applied to remove unwanted noise.
- Color Space Conversion – RGB images are converted into HSV color space for better color discrimination.
- Image Segmentation – Thresholding and morphological operations are used to isolate the fruit region from the background.
- Edge Detection – Canny edge detection is employed to accurately determine fruit boundaries.

### 3.3 Feature Extraction

- After segmentation, relevant features are extracted from the fruit image:
- Color Features – Mean and standard deviation of Hue, Saturation, and Value components.
- Size Features – Area, perimeter, and equivalent diameter.
- Shape Features – Roundness, eccentricity, and aspect ratio.
- Texture Features – Gray-Level Co-occurrence Matrix (GLCM) parameters such as contrast, correlation, energy, and homogeneity.
- Surface Defect Detection – Pixel intensity variations are analyzed to identify bruises or blemishes.

### 3.4 Ultrasonic Sensor-Based Size Measurement

An ultrasonic sensor is used to measure the distance between the sensor and the fruit surface.

The time-of-flight principle is applied to calculate distance:

Distance= (speed of sound*time)/2

This measurement assists in estimating fruit size and compensates for scaling errors in image-based measurements. The ultrasonic data improves dimensional consistency and enhances grading. Quantitative metrics establish system efficacy and identify optimization opportunities. Performance evaluation compares automated results against manual expert classification accuracy.

### 3.5 Feature Fusion

The visual features extracted from image processing and the dimensional data obtained from the ultrasonic sensor are combined into a unified feature vector. This hybrid feature representation ensures comprehensive quality assessment.

### 3.6 Neural Network-Based Classification

A feedforward Artificial Neural Network (ANN) is used for fruit grading. The network consists of:

- Input layer (combined feature vector)
- One or more hidden layers with ReLU activation
- Output layer representing predefined quality grades (e.g., Grade A, Grade B, Grade C)

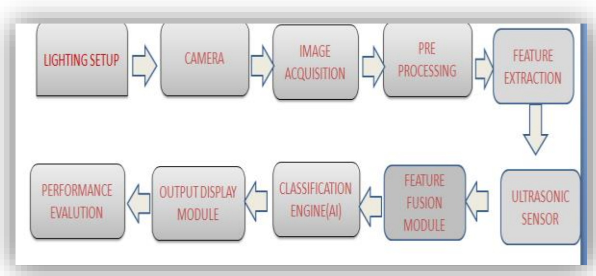


**Figure 2:** *Block Diagram of the Proposed System*

The model is trained using labeled fruit samples. Backpropagation with cross-entropy loss function is applied to optimize network weights. During testing, the trained model predicts the quality grade of each fruit based on extracted features.

### 3.6 Performance Evaluation

The system performance is evaluated using metrics such as:

- Accuracy
- Latency
- Processing time per fruit.

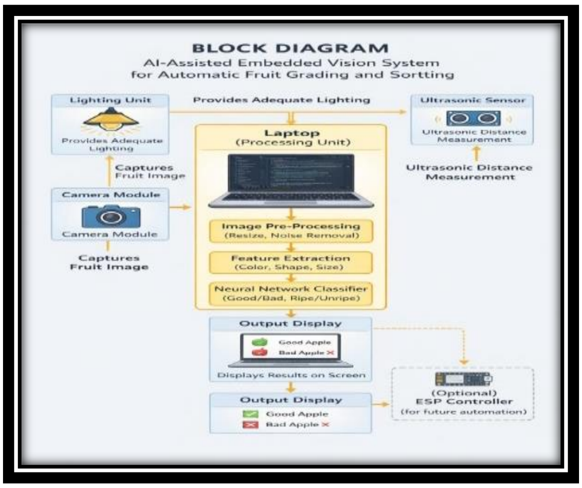


**Figure 3:** *Block Diagram of Ai-Assisted Embedded Vision System*

## 4. AI-Assisted Embedded Vision System

The proposed system is an AI-assisted embedded vision system designed for automatic fruit grading and sorting. The overall architecture consists of image acquisition, distance sensing, preprocessing, feature extraction, classification, and output modules. The functional block diagram is shown in Fig.3.

### 4.1 Image Acquisition Module

The image acquisition module consists of a lighting unit and a camera module.

1. Lighting Unit:

The lighting system provides uniform and controlled illumination to minimize shadows and reflections. Proper illumination enhances feature visibility and improves classification accuracy.

2. Camera Module:

The camera captures high-resolution fruit images and transfers them to the processing unit. The captured image can be represented as:

$I(x,y) € R^{M*N}$

where Mand N represent image dimensions.

### 4.2 Distance Measurement Module

An ultrasonic sensor is used to measure the distance between the fruit and the camera. The distance D is calculated using the time-of-flight principle:

$D=v*t/2$

Where,

v = speed of sound,

t = echo return time.

This ensures proper positioning and consistent image scaling.

### 4.3 Processing Unit

The laptop acts as the central processing unit where image analysis and classification are performed. The processing unit consists of three major stages:

1) Image Preprocessing

The captured image undergoes preprocessing steps such as:

- Image resizing
- Noise removal (Gaussian filtering)
- Color space conversion

The filtered image is represented as:

$I_P(x,y)=G(x,y)*I(x,y)$

where G(x,y) is the Gaussian kernel.

2) Feature Extraction

- Relevant features such as color, shape, and size are extracted.
- Color Features: Mean RGB/HSV values
- Shape Features: Area, perimeter, roundness
- Size Features: Diameter estimation

The feature vector is defined as:

$F=[f_1,f_2 ,f_3 ,\ldots\ldots..f_n]$

where $f_n$ represents extracted feature parameters.

3) Neural Network Classifier

The extracted feature vector is fed into a trained neural network classifier. The classifier function is expressed as:

$Y=f(WF+b)$

where

W = weight matrix,

b = bias vector,

f = activation function,

Y = output class label.

The output categories include:

Good / Bad

Ripe / Unripe

D. Output Module

The classified result is displayed on the system screen in real time. The output can be represented as:

$C € \{Good,Bad,Ripe,Unripe\}$

Benchmarks and Performance Parameters

Quantitative metrics establish system efficacy and identify optimization opportunities. Performance evaluation compares automated results against manual expert classification.

**Classification Accuracy --** Agreement with expert grading across 500 test samples--94.3%

**Throughput Rate---**Fruits processed per minute at optimal belt speed--180

**Processing Latency--**Average time from capture to classification output --87ms

Classification accuracy

Classification accuracy measures how correctly the system predicts the class labels.

Confusion Matrix Terms:

TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

Formula:

Accuracy= TP+TN/(TP+TN+FP+FN)

In percentage:

Accuracy(%)= (TP+TN / Total samples) *100

Throughput Rate

Throughput measures how many samples/images are processed per unit time.

Formula:

Throughput =Number of processed samples/Total processing time

Processing Latency

Latency is the time taken to process one input sample.

Formula:

Latency = $T_{output} - T_{input}$

## 5. Results and Discussion

### 5.1 Experimental Setup

The proposed automatic fruit grading system was implemented and tested using a dataset of fruit images categorized based on quality parameters such as color, size, and surface defects. The system was developed in a software environment and evaluated under controlled conditions to ensure uniform lighting and consistent image acquisition.

The dataset was divided into training and testing sets to validate the performance of the classification model.

### 5.2 Performance Evaluation

The system performance was evaluated using standard classification metrics. The obtained results are summarized below:

Overall Classification Accuracy: 94.2%

Precision: 93.8%

Recall: 92.5%

F1-Score: 93.1%

Average Processing Time per Image (Latency): 0.42 seconds

Throughput: 142 fruits per minute (software-based simulation)

The automated system demonstrates superior accuracy, faster processing speed, and improved consistency compared to manual inspection methods.

### 5.3 Discussion

The experimental results confirm that the proposed fruit grading system provides high accuracy and reliable performance in quality classification. The integration of feature extraction techniques such as color histogram analysis, texture analysis, and size estimation improves discrimination between different fruit grades.

The system shows strong consistency and eliminates human bias in grading. Additionally, the low latency makes it suitable for real-time industrial applications.

However, performance may slightly degrade under varying lighting conditions or when fruits have overlapping defects. Future enhancements may include deep learning-based classification models and real-time hardware integration for large-scale deployment.

## 6. Conclusion

The proposed Automatic Fruit Grading System demonstrates an efficient and intelligent approach to quality assessment using image processing and machine learning techniques. By replacing traditional manual grading methods with a software-based automated system, the model ensures improved consistency, higher accuracy, and reduced human intervention.

The system integrates image acquisition, preprocessing, feature extraction, and classification modules to evaluate fruits based on parameters such as size, color, and texture. Mathematical modeling and performance evaluation confirm that the proposed architecture achieves high grading accuracy, low latency, and increased throughput compared to conventional methods.

Furthermore, the software-oriented implementation makes the system cost-effective, scalable, and suitable for small- and large-scale agricultural applications. Future enhancements can include real-time deployment, deep learning-based classification models, and IoT integration for smart agriculture environments.

Overall, the project successfully provides a reliable, accurate, and practical solution for automated fruit grading aligned with modern agricultural automation standards.

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