AUTOMATIC SORTING AND GRADING OF FRUITS BASED ON MATURITY AND SIZE USING MACHINE VISION AND ARTIFICIAL INTELLIGENCE

ABSTRACT

This paper introduces a computer vision-based system designed for the automated grading and sorting of agricultural products based on their size and maturity. The proposed machine vision system aims to replace traditional manual methods commonly used for sorting and grading fruits. Manual inspection often struggles to ensure consistency in grading and uniformity in sorting. To address these challenges and enhance the quality of fruit grading, image processing and machine learning algorithms can be employed. Key attributes such as the fruit's shape, color, and size can be analyzed to enable a non-destructive approach to classification and grading. Automation of these processes becomes feasible when standardized criteria for grading are established. Such systems offer faster operations, save time, and reduce manual labor, making them highly valuable to meet the increasing demand for premium-quality agricultural produce.

Keywords: *Sorting, grading, maturity level, artificial intelligence, machine vision technology*

1. INTRODUCTION

India is the second highest productions of the fruits and vegetables. Ensuring high-quality fruits and vegetables are delivered to consumers is achieved through effective sorting and grading before packaging. Fruits and vegetables are sorted based on similarities in size, shape, maturity, and defect features, while grading is determined by their commercial value. Currently, sorting and grading are typically performed manually through visual inspection before transportation. This manual process is labour-intensive, time-consuming, and prone to inconsistency and inaccuracies due to human judgment. By leveraging AI and computer vision, sorting and grading can be automated, ensuring consistent quality while analysing size, shape, and maturity, ultimately delivering high-quality produce to customers before packaging.

Grading and sorting of fruits using artificial intelligence (AI) and machine vision are essential processes in the agriculture and food industries. These technologies help in automating the assessment of fruit quality, classifying them based on size, color, shape, ripeness, and external defects, which can significantly improve efficiency, consistency, and reduce human error**.** Machine vision technology is revolutionizing agriculture and food processing, particularly in the sorting and grading of fruits is essential for classifying produce accurately (M.A. Ashraf *et al.,* 2011). The product quality, streamlining the supply chain, and reducing food waste is maintained by machine vision (A. Ktenioudaki *et al.,* 2021) emphasizes. Machine vision has rapidly advanced in the inspection of agri-food products, including meat, fish, and especially fruits and vegetables (Sun, 2007; Du & Sun, 2009; Quevedo *et al*., 2008a; Quevedo & Aguilera, 2010). Unlike manual inspection, automated systems provide a more consistent and objective analysis. The quality of fresh or processed fruits and vegetables is determined by various physicochemical properties that influence consumer appeal. These include factors such as ripeness, size, weight, shape, color, blemishes or diseases, stem presents, seeds, and sugar content. These attributes affect the product's visual appeal, nutritional and sensory qualities, and its suitability for preservation. Traditionally, trained inspectors visually assessed these qualities, but modern commercial vision systems are now able to evaluate most of these factors more effectively (Du & Sun, 2006).

Advanced computer vision and machine learning algorithms are now being utilized to assess multiple characteristics of fruits, enabling precise categorization and grading decisions [L. Kaiyan *et al.,* 2021]. Color analysis, a technique in computer vision, employs color cameras and algorithms to identify color features in images, making it an effective method for automating the sorting and grading process of fruits [M.F. Ibrahim *et al*., 2016 and D. Unay e*t al.* 2022]. The distributors select only high-quality products for consumers. Additionally, distributors help suppliers meet appearance control standards (Clement *et al.,* 2012). Therefore, efficient, reliable, and non-destructive methods are essential for detecting and grading fruits and vegetables accurately (Wu & Sun, 2013).

Traditional machine learning algorithms have proven effective in classifying data based on a limited set of visible features. Additionally, (S. Palei *et al*., 2023), analyzed and compared various methods for predicting citrus diseases, highlighting current results, existing limitations, and offering suggestions for future research in citrus fruit grading related to disease identification. Techniques like GoogLeNet, ResNet50, and AlexNet are commonly employed for grading vegetables (Bhargava & Bansal, 2021b), while multiple segmentation, feature extraction, and classification methods are used to grade and sort different apple varieties (Bhargava A *et al*., 2020b). In industrial settings, machine vision systems (MVS) play a key role in detecting, assessing, and monitoring objects (Golnabi & Asadpour, 2007). (Martynenko 2008) developed a system to estimate changes in the density and porosity of ginseng roots during drying, eliminating the need for intricate scanning electron microscope imaging.

Image processing and analysis serve as the core tasks of computer algorithms and methods used to achieve the desired vision through various classifications and measurements. Characteristics like color, shape, and size are integrated to enhance the accuracy of classification, significantly benefiting the food industry. Normally, by increasing the characteristics used, it is possible to increase the performance of the proposed methods. However, automating the inspection of agricultural produce comes with unique challenges due to its biological diversity. Unlike manufactured products that often have uniform colors, shapes, and sizes, fruits and vegetables display considerable variation. Even fruits picked on the same day from the same tree can differ in color, size, and shape. Furthermore, post-harvest, fruits and vegetables undergo natural changes in color and texture based on their maturity and storage conditions (Cubero, 2011).

For the sorting and classification of fruits, there are different parameters such as color, weight, size, shape, and density. Research on fruit quality classification based on color, size, and volume is nearing completion in the laboratory but has not yet been implemented in practical applications. The assessment of fruit quality remains unresolved. The classification of fruits based on color, volume, size, shape, density etc. This categorization system, utilizing image processing, integrates artificial intelligence components such as a camera, computer vision, and artificial neural network. The system employs captured fruit images to ascertain mass, volume, and surface defects on the fruit. Therefore, this review paper aims to present automatic sorting and grading of fruits based on maturity and size using machine learning methods.

2. GRADING OF FRUITS

Grading of fruits using machine vision and AI is an innovative approach in image processing, pattern recognition and deep learning techniques to evaluate fruit quality based on various parameters. Color is a critical factor in fruit grading as it strongly correlates with the ripeness and overall quality of the produce (Masi *et al.,* 2019). Initial methods for grading citrus fruits often relied on traditional color segmentation techniques, focusing on attributes like hue and saturation for sorting purposes (García *et al*., 2009).

The advent of artificial intelligence, particularly Convolutional Neural Networks (CNNs), has revolutionized fruit grading processes. CNNs, first highlighted by (Krizhevsky *et al.,* 2012), are deep learning models that excel in analyzing visual data by detecting spatial hierarchies in images. These capabilities make CNNs especially suitable for tasks like defect detection and fruit grading, where visual features such as texture, color, and shape play a key role (Zhao *et al*., 2018). In citrus fruit sorting, CNNs have been effectively trained to detect defects like scarring, discoloration, and deformities (Zhang *et al*., 2021). They also enable precise classification based on ripeness levels, color, and size, achieving high accuracy rates in grading tasks (Zhao *et al*., 2018).

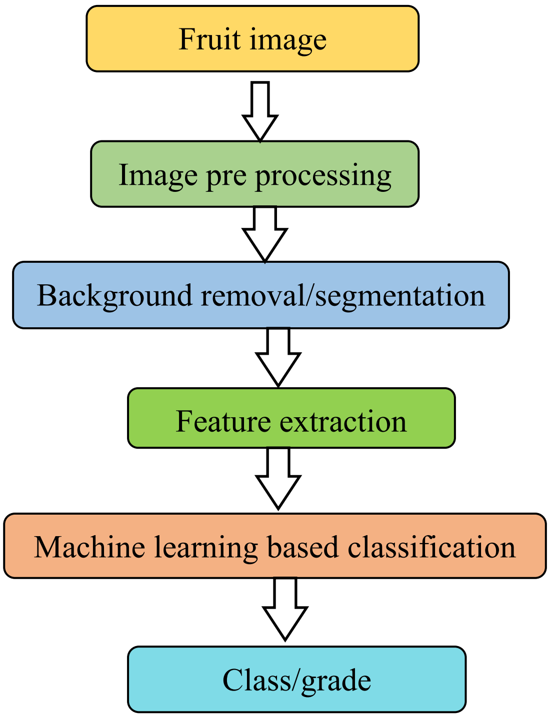

Figure. 1 Framework for the grading of fruits

2.1 Image Acquisition: In the image acquisition high-definition RGB cameras, strategically mounted on a conveyor belt system, which are used to capture images of fruits for grading purposes. These images showcase a range of defects, including scarring, discoloration, and deformations. Additionally, the fruits are recorded at various stages of ripeness, exhibiting diverse sizes, shapes, and weights. This setup ensures a comprehensive dataset for analysis, enabling accurate identification and classification of fruits based on their quality attributes are essential (Patel, P. 2017).

2.2 Image pre-processing: Image processing includes several preprocessing steps aimed at enhancing image quality. These steps ensure a clear image, making it easier to segment the fruit accurately. Binarization is also applied, as certain features are extracted more effectively in the binary domain (K. Khurshid *et al.,* 2019). Removal of noise is done in the pre-processing to attain high quality features.

2.3 Image feature extraction: The extraction of different quality features is taken from the pre-processed images, to get the high quality of the fruits by those features extraction. The features are edge features- which uses the different types of filters to detect the edges of the fruit's detect the boundary for identification of defects, colour features- the extraction of the colour features from RGB, HSV models are used to get the better colour alteration, texture features- entropy filter, statistical filter are used to find the texture of the fruit classification.

2.4 Classification: The feature extraction image is classified to know the fruit is good or bad. Classification is done to assign each fruit to a category or grade.

Table:1 case study for the grading of fruits using AI and machine vision technologies

Author and year	Fruit type	Data size	Data acquisition	Classification algorithm	Accuracy
Nazrul Ismail, Owais A. Malik, 2022	Apples, bananas	8791 apples, 3946 bananas	Raspberry Pi camera module	ResNet, DenseNet, MobileNetV2, NASNet and EfficientNet	96.7% apples, 93.8% bananas
Pallavi U. Patil	Dragon fruit	NA	raspberry pi function	CNN, ANN, and SVM	CNN accuracy

et al., 2021					
Anuja Bhargava & Atul Bansal 2020	Apple	NA	NA	k-NN, logistic regression (LR), SRC, and SVM	98.42% SVM
Anuja Bhargava & Atul Bansal 2019	Avocados, apple, banana, oranges	19779	NA	(SVM), (ANN), (SRC), and (k-NN).	95.72% (SVM),
R. Thendral and A. Suhasini, 2017	Lemon, guava	NA	CCD camera	SVM	96%

(Nazrul Ismail, Owais A. Malik, 2021), In this study introduced a machine vision system utilizing advanced deep learning and stacking ensemble techniques to enable non-destructive, cost-effective inspection of fruit freshness and appearance. Models such as ResNet, DenseNet, MobileNetV2, NASNet and EfficientNet were trained and tested to determine the best option for fruit grading with EfficientNet achieving high accuracy-99.2% for apples and 98.6% for bananas on test datasets. The system operates in real-time with a Raspberry Pi, camera, and touchscreen, segmenting and grading individual fruits effectively. Real-world testing showed 96.7% accuracy for apples and 93.8% for bananas, surpassing previous methods and confirming its effectiveness.

(Pallavi U. Patil *et al.* 2021), In this study machine learning-based grading and sorting techniques is used for dragon fruit, with CNN, ANN, and SVM algorithms. These methods classify fruit quality based on features such as shape, size, weight, color, and disease presence. Additionally, a Raspberry Pi system is used to count the total fruits in a bucket, sorting them by maturity level with machine learning.

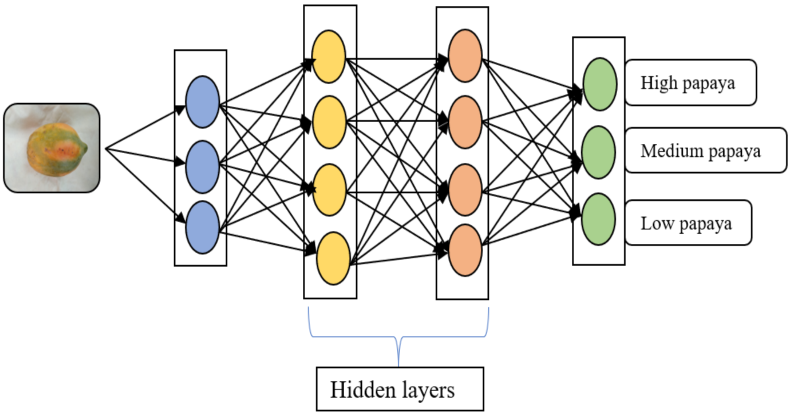

Figure. 2 Structure of CNN Model for Grading of Fruits

(Anuja Bhargava & Atul Bansal 2020), This study introduced a novel approach for assessing the quality of Six apple varieties—Fuji, Granny Smith, York, Golden Delicious, Jonagold, and Red Delicious—are analyzed. Image segmentation is performed using the grab-cut method and c-means clustering. Various features, including statistical, textural, geometrical, discrete wavelet transform, histogram of oriented gradients, and Laws' texture energy, are then extracted for classification and analysis. Principal component analysis refines the feature selection process. Classification into fresh or rotten categories is performed using k-NN, logistic regression (LR), SRC, and SVM classifiers, validated via cross-validation. SVM achieves the highest accuracy: 92.90% (k = 5), 98.42% (k = 10), and 95.27% (k = 15). The results demonstrate that proper feature extraction and selection significantly enhance performance, making this method adaptable for evaluating multiple fruit types.

(Anuja Bhargava & Atul Bansal 2019), In this study designed a system to classify four types of fruits and assess their quality ranks. The process begins with extracting red, green, and blue color values from fruit images, followed by background removal using a split-and-merge algorithm. The system then extracts 30 features, including color, statistical, textural, and geometrical attributes, with geometrical features. Four classifiers—k-nearest neighbor (k-NN), support vector machine (SVM), sparse representative classifier (SRC), and artificial neural network (ANN)—are employed for classification. The system was tested on four fruit datasets: apples (4359 images, 2342 defective), avocados (918 images, 491 defective), bananas (3805 images, 2224 defective), and oranges (3050 images, 1590 defective). Using k-fold cross-validation, the highest detection accuracies were achieved with SVM (98.48%), ANN (91.03%), SRC (85.51%), and k-NN (80.00%) for k=10k = 10k=10. For quality grading among Rank 1, Rank 2, and defective fruits, the maximum accuracies were 95.72% (SVM), 88.27%

(ANN), 82.75% (SRC), and 77.24% (k-NN). The results demonstrate SVM's superior performance, providing highly encouraging outcomes comparable to advanced methods.

(R. Thendral and A. Suhasini, 2017), In this studied a machine vision technology developed to ensure the high-quality oranges which are selected for export by effectively identifying and classifying skin defects. Key grading parameters such as shape, size, color and texture — determine the quality and market value of fruits. Combining these parameters improves grading accuracy. This study introduces an orange surface grading system (normal vs defective) using color and texture features. Feature selection was optimized using a wrapper approach with a genetic algorithm, which identified the most informative features for classification. Performance was tested using support vector machine, backpropagation neural network, and auto-associative neural network (AANN), with AANN achieving the highest accuracy of 94.5%.

3. SORTING OF FRUITS

Color and size are critical features for effective classification and sorting, as highlighted by (Khojastehnazhand *et al.,* 2010). Estimating fruit size also supports the planning of packaging, transportation, and marketing activities. Key physical attributes for sizing agricultural products include volume, mass and projected areas, which are essential in sizing systems (Tabatabaeefar & Rajabipour, 2005; Wright *et al.,* 1986; Safwat & Moustafa, 1971). Automated fruit grading leverages machinery and computer vision technology to streamline the grading process, focusing on precise quality evaluation, defect identification, and uniformity. This approach aims to enhance the speed of processing while consistently delivering high-quality fruit, effectively reducing operational costs. In today's fruit production and processing sectors, automation has become essential, ensuring quality consistency and minimizing waste through accurate detection and separation of defective fruits. By optimizing workflows and increasing throughput, it boosts productivity and cost efficiency, meeting the demands of the modern fruit supply chain. (Benjamin Oluwamuyiwa Olorunfemi *et al.,* 2024).

Image acquisition serves as a crucial initial step in fruit sorting, involving the capture of fruit images through a range of cameras and sensors (Benjamin Oluwamuyiwa Olorunfemi *et al.,* 2024). Cameras operating within the visible spectrum (400–700 nm) are utilized to capture essential attributes like color, shape, size, and surface flaws (L. Poudwal *et al.,* 2022). Recent innovations in this area have advanced imaging techniques, including multi-spectral fusion, which combines data from different spectral bands, such as visible, near-infrared (NIR), and hyperspectral, to provide a thorough characterization of fruit properties (S. Sabzi *et al*., 2018., F. Tan *et al.,* 2023). Automation technology has also progressed, with machine learning, deep learning, new sensor technology, cloud computing, and software tools making automation more accessible and economical. In light of this, recent research has increasingly focused on applying machine learning and deep learning methods to enhance the accuracy of fruit identification and classification.

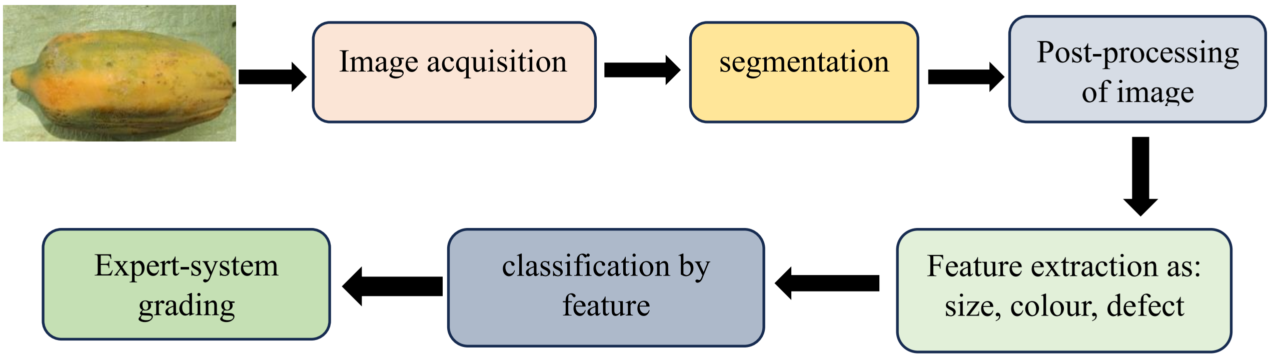

Figure. 3 Flow chart for the sorting of fruits using machine vision

Table: 2 Case studies for the sorting of fruits using AI and machine vision technologies

Author and year	Fruit type	Data acquisition	Classification algorithm
Zheng Zhou *et al.,* 2023	fruit	CCD camera	Artificial intelligence
Nguyen Truong Thinh *et al.,* 2020	Mango	CCD cameras	C-language programming, computer-vision and artificial neural networks
Nguyen Duc Thong *et al.,* 2019	Mango	CCD camera	C-language programming, computer vision and AI
Hafiz Muhammad Tayyab Abbas *et al.,* 2018	apple	CCD camera	MATLAB

(Zheng Zhou *et al.* 2023), In this study focused on AI applications in on-farm sorting and transportation of postharvest fruit, highlighting its potential to enhance sorting speed, accuracy, and reduce postharvest losses. The paper examines AI's role in addressing on-farm challenges, focusing on the use of sensors and data acquisition techniques to support AI-driven tasks. Comparative analysis of AI models from previous studies is provided to determine effective approaches. Additionally, the benefits and limitations of AI in on-farm applications are discussed, along with recommendations for future research. Aim to encourage advancements in automated on-farm fruit sorting and transport systems.

(Nguyen Truong Thinh *et al.* 2020), The study focused on three commercial mango varieties—Cat Chu, Cat Hoa Loc, and Green Skin Mango—to develop a more effective classification system. Traditional methods based on color and volume fail to meet the standards for commercial mango quality and accuracy. The proposed system uses image processing and artificial intelligence techniques, including CCD cameras, computer vision, and artificial neural networks, to classify mangoes by color, size, shape, volume, and density. Captured mango images are processed to analyze surface defects, calculate mass and volume, and assess defect percentages, determining suitability for export, domestic use, or recycling. This research aims to design an automated mango classification system with high accuracy and quality control capabilities, providing a reliable solution for packaging and market evaluation. The system integrates advanced algorithms and statistical methods, ensuring an efficient and accurate approach to mango quality assessment.

(Nguyen Duc Thong *et al.* 2019), In this study developed an automated system to classify three major commercial mango species in Vietnam by quality. Using image processing and AI, the system assesses mangoes based on colour, volume, size, shape, and density. It employs CCD cameras, computer vision, and neural networks to analyze mango images, identifying mass, volume, defects, and maturity indicators like density. The ultimate goal is to optimize mango quality control before packaging and export, ensuring only high-quality mangoes reach the market.

(Abbas, H.M.T *et al.* 2019), The study focused on the automated fruit sorting using image processing is to enhance sorting quality, maintain product standards, boost production, and reduce labor demands. For such a system, rapid and accurate feature detection and efficient fruit processing are essential. This paper provides a thorough review of current advancements in automated sorting and grading for agricultural products, and proposes a comprehensive, end-to-end solution for efficient, image-based fruit sorting and grading.

4. CONCLUSION

AI technologies have significantly expanded in automating various on-farm sorting, grading and transportation tasks. Recently, AI has enhanced the accuracy in post-harvest fruit sorting and transportation on farms. This review key work to explore the current use of AI in these on-farm processes, analysing the challenges faced, and discussing future opportunities. Key insights regarding data collection sensors, AI model deployment, and their respective advantages are discussed. Additionally, the study addresses limitations and suggests future research paths to deepen understanding and support the development of autonomous on-farm sorting and transportation systems. Given rising labour costs and the market's demand for high-quality produce, AI-driven systems are expected to play a main role in precision agriculture for on-farm operations. With the ongoing advancements in AI, its application in on-farm sorting and transportation is likely to become widespread in the near future.

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