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Automatic Sorting and Grading of Fruits Based on Maturity and Size Using Machine Vision and Artificial Intelligence

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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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: Artificial intelligence; grading; machine vision technology; maturity level; sorting.

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.

Most fruit sorting and grading classifiers have been developed using machine learning algorithms and neural networks, such as Convolutional Neural Networks (CNNs). These models utilized labeled training data to create predictive systems based on fruit characteristics. Traditional machine learning algorithms, including Support Vector Machine (SVM) by (Gurubelli, Y et al., 2020), Random Forest (RF) by (Lu, Y and Lu, R. 2018), K-Nearest Neighbors (KNN) by (N. Çetin, K et al., 2022), and Decision Tree (DT) by (Jahanbakhshi, A et al., 2020), have proven effective for tasks that involve categorizing data based on a limited set of visible characteristics by the study on (Lu, Y. and Lu, R., 2018). (Pande, A et al., 2019), gave an approach on a grading system for an apple dataset was developed using the pre-trained Inceptionv3 deep learning model, achieving a top-5 accuracy of 90% in classifying apples into four grades. This system utilized a transfer learning approach, leveraging the Fruit 360 dataset to grade a self-collected dataset comprising 150 apples. (Tian, Y et al., 2019), study have also been utilized used the deep learning techniques to detect lesions in apple fruits.

An alternative approach, as described in (Hu, Z et al., 2020), involved the use of 3D surface meshes to train and test Convolutional Neural Networks (CNNs) for identifying bruised apples. The study reported achieving a best predictive model accuracy of 97.67%. Deep learning has also been investigated for postharvest classification of Cavendish bananas, as detailed in (Ucat, R.C. and Cruz, J.C.D., 2019). A self-designed Convolutional Neural Network was trained on four classes using a dataset of 1,116 images, of papaya fruits achieving an average test accuracy of 90%. Additionally, a deep learning-based maturity classification system for papaya fruits has been proposed in (Behera, S.K et al., 2021).

Advanced computer vision and machine learning algorithms were utilized to assess multiple characteristics of fruits, enabling precise categorization and grading decisions, as demonstrated by (L. Kaiyan et al., 2021). Color analysis, a technique in computer vision, was employed using color cameras and algorithms to identify color features in images, demonstrating its effectiveness in automating the sorting and grading process of fruits, as shown in (M.F. Ibrahim et al., 2016) and (D. Unay et al., 2022; Ktenioudaki et al., 2021). Traditional machine learning algorithms had proven effective in classifying data based on a limited set of visible features. Additionally, in the study of (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.

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 as highlighted by (Masi et al., 2019). In the study by (Zhao et al., 2018), CNN were identified as particularly effective for tasks such as defect detection and fruit grading, where visual features like texture, color, and shape are crucial. Similarly, (Zhang et al., 2021; 2018) demonstrated that CNN were successfully trained for citrus fruit sorting, enabling the detection of defects such as scarring, discoloration, and deformities. These networks also facilitated precise classification based on attributes like ripeness, color, and size, resulting in high accuracy rates for grading tasks, as highlighted by (Zhao et al., 2018).

2.1 Image Acquisition

Image acquisition involved the use of high-definition RGB cameras strategically mounted on a conveyor belt system to capture images of fruits for grading purposes. These images displayed a variety of defects, such as scarring, discoloration, and deformations. Furthermore, fruits were recorded at different stages of ripeness, reflecting a range of sizes, shapes, and weights. This setup provided a comprehensive dataset for analysis, facilitating accurate identification and classification of fruits based on their quality attributes, as highlighted by (Patel, P., 2017).

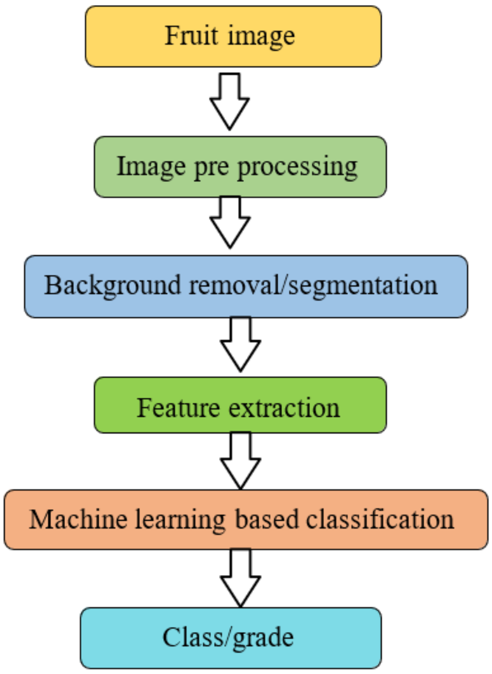

Fig. 1. Framework for the grading of fruits

Table 1. Case study for the grading of fruits using AI and machine vision technologies

Author	Fruit	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 et al., 2021	Dragon fruit	NA	raspberry pi function	CNN, ANN, and SVM	CNN with high accuracy
Anuja Bhargava and Atul Bansal, 2020	Apple	NA	NA	k-NN, logistic regression (LR), SRC and SVM	98.42% SVM
Anuja Bhargava and 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% accuracy

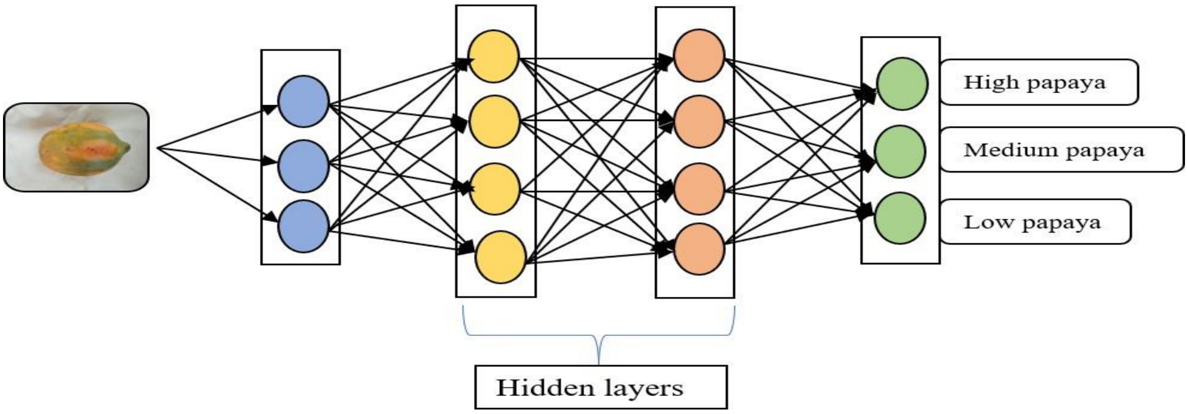

Fig. 2. Structure of CNN model for grading of fruits

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 by (K. Khurshid et al., 2019). Removal of noise is done in the pre-processing to attain high quality features is also been done.

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.

(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.

In the study (Pallavi U. Patil et al., 2021), used the machine learning-based grading and sorting techniques of 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.

In this study (Anuja Bhargava and Atul Bansal 2020), 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, 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.

In this study (Anuja Bhargava and Atul Bansal 2019), 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.

In this study (R. Thendral and A. Suhasini, 2017) developed a machine vision technology 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

(Majeed and Waseem, 2022) describe on-farm sorting as a crucial post-harvest process that aims to enhance produce quality and marketability. According to the authors, this process involves first removing defective items, such as those that are damaged, diseased, or rotten. Subsequently, the remaining produce is organized into bins or trays based on specific characteristics, including size, color, maturity, and ripeness, ensuring uniformity for market presentation and further processing. (Idama and Uguru 2021) emphasize that deploying artificial intelligence (AI) in post-harvest handling can accelerate processes, minimize post- harvest losses, and reduce the risk of mechanical injuries. (Bader and Rahimifard 2020) further highlight that AI integration improves operational efficiency while enhancing safety and facility conditions for workers handling fresh horticultural produce. (Maheswari et al., 2021) highlight that numerous AI-based solutions have been developed to maintain the quality of fresh fruit products at both on-farm and post-harvest stages. Over the past few years, significant efforts have been directed towards advancing automated agricultural systems capable of efficiently performing labor-intensive field tasks, including fruit yield estimation, as discussed by (Maheswari et al., 2021); shoot thinning, as noted by (Majeed et al., 2020, 2021); non-destructive defect detection, as reported by (Nturambirwe and Opara 2020); and mechanical harvesting, as illustrated by (Zhang et al., 2020). However, current reviews provide limited information on the advancements of AI techniques, such as computer vision, machine learning, and deep learning, specifically for on-farm fruit sorting and transportation. (Wendel et al., 2018), (Gabriëls et al., 2020), and (Kang and Gwak 2021) state that conventional fruit sorting primarily relies on visual assessment, considering factors such as ripeness, quality, decay, disease, and injury. According to (Rysz and Mehta 2021), on-farm sorting is labour-intensive, prone to low productivity, and susceptible to human fatigue. Additionally, it is influenced by the inspector's experience, often leading to variability in product quality and failure to consistently meet established standards.

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 as highlighted by (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 as highlighted by (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 as stated by (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 as highlighted by (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.

In this study (Zheng Zhou et al., 2023), 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.

The study (Nguyen Truong Thinh et al., 2020), 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.

In this study (Nguyen Duc Thong et al., 2019), 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.

The study (Abbas, H.M.T et al., 2019), 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.

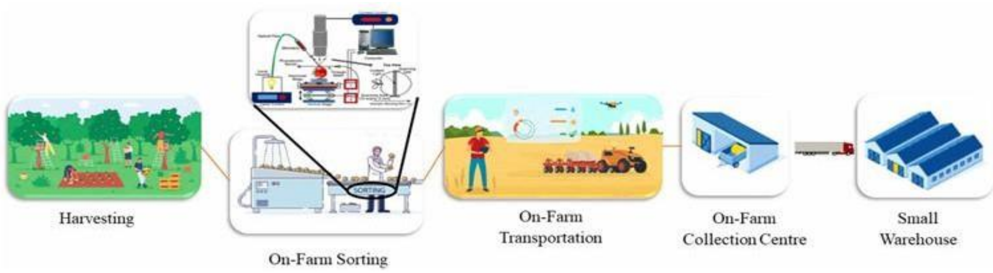

Fig. 3. A flowchart outlining the steps involved in on-farm sorting and transportation (Zhou, Z et al., 2023)

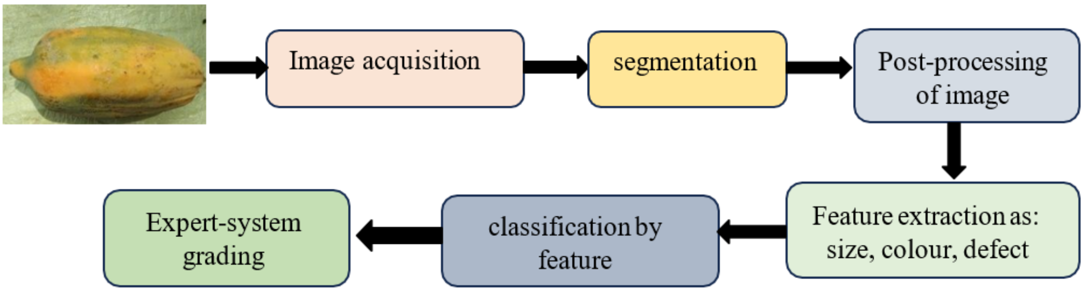

Fig. 4. Flow chart for the sorting of fruits using machine vision

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

Author	Fruit	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

4. LIMITATIONS FOR AI MODELS IN ON-FARM TRANSPORTATION

- (Tripathi, M.K and Maktedar, D.D. 2020), noted that the level of small-scale agricultural enterprises and individual farmers, the adoption of advanced technologies has been relatively limited. Two primary obstacles hindering their implementation are the increased overall costs associated with these technologies and the necessity to acquire specialized skills. Therefore, it is increasingly important to design cost-effective and user-friendly solutions that enable these enterprises and farmers to better leverage modern technological advancements.
- (Zhou, Z et al., 2023) noted that the primary sensors used for on-farm sorting, such as RGB and CCD cameras, are limited to detecting surface-level features like shape, color, and size. To enable broader adoption on small farms, cost-effective sensors with high throughput capabilities are necessary. Advanced technologies like hyperspectral cameras, lasers, and NIR sensors, commonly used in factory sorting lines for defect detection, can be adapted to enhance the detection of both surface and internal defects in fruits and vegetables for on-farm sorting systems.
- Another challenge in on-farm sorting AI models lies in the datasets used for training. Previous studies primarily relied on datasets created for specific research purposes, often with a limited selection of fruit varieties and cultivars. To ensure dataset diversity, fruit samples were randomly chosen, and their quality was manually assessed and classified by experts (Caladcad et al., 2020; Mansuri et al., 2022; Wang et al., 2022).

5. 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 gap 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.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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