Revue d'Intelligence Artificielle
Vol. 37, No. 2, April, 2023, pp. 465-474
Journal homepage: http://iieta.org/journals/ria

Computer Intelligence-Based Fruit Grading: A Review

Ashoka Kumar Ratha[1], Nalini Kanta Barpanda[1], Prabira Kumar Sethy[1*], Gowni Sharada[2], Santi Kumari Behera[3]

[1] Department of Electronics, Sambalpur University, Jyoti Vihar, Burla 768019, Sambalpur, Odisha, India
[2] Department of Information Technology, Malla Reddy College of Engineering & Technology, Hyderabad 500100, India
[3] Department of CSE, VSSUT, Burla 768018, Sambalpur, India

Corresponding Author Email: prabirsethy.05@gmail.com

https://doi.org/10.18280/ria.370223

Received: 20 February 2023
Accepted: 31 March 2023

Keywords:
fruits identifications, fruits classifications, defect discriminations, fruit grading, image processing

ABSTRACT

India is the second-largest fruit producer in the world. But, fruit identification, classification, and grading are carried out manually. Hence, most of the harvested fruit was wasted due to human perception subjectivity because there needed to be more qualified workers. Therefore, the fruit sector must impose an automated fruit detection system to distinguish among different types of fruits based on their variety, class, maturity, and quality. An automated system may be created with the use of appropriate image processing ideas and machine learning strategies for grading and quality inspection of fruits. With an emphasis on the advancement of state-of-the-art, this study provides a quick examination of the methodologies put out in the research publications from the last couple of years. Various methods are used to compare the relevant studies.

1. INTRODUCTION

Due to India's varied environment, fresh fruits and vegetables are always available. After China, it produces the most fruit and vegetables worldwide. According to the National Horticulture Board's National Horticulture Database (@3rd Advance Estimates), total horticulture production is expected to reach 342.33 million tonnes in 2021-22, which is 7.73 million tonnes (or 2.3% more) than in 2020-21 (final). The production of fruits is expected to reach 107.24 million tonnes, a rise from 102.48 million tonnes in 2020-21 [1]. Figure 1 shows the rate of horticultural crop production over the last three years.

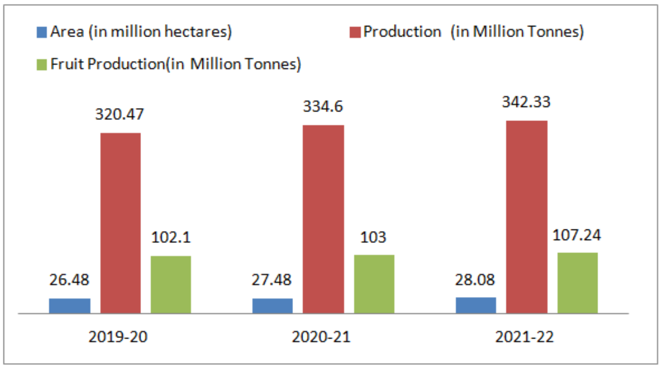

Figure 1. Rate of horticulture crops production in India

The Food and Agricultural Organization (FAO) (2020) reports that this nation is the number one in the world with regard to the production of bananas, papayas, and mangoes (including Mangosteens and Guavas). India's fruit production from 2012 to 2021 (at the 3rd advance estimate) is depicted in Figure 2 providing a comprehensive explanation of the bar chart. An incredible amount of fruit is produced in a short period of time. However, at the same time, there is a high possibility of post-harvest loss and a need for more storage facilities due to a shortage of cold storage and specialized labor. However, this is a significant limitation.

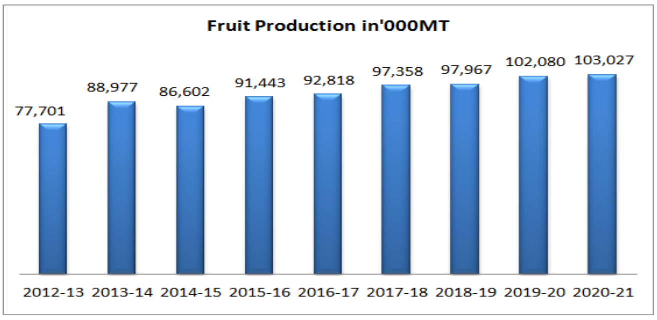

Figure 2. Yearly fruit production (in '000 tonne) in India 2012 to 2021(@3rd advanced Estimate)

Figure 3 indicates India's state-by-state production of fruits from 2012 to 2020, whereas Figure 4 indicates the production of three key fruits, Papaya, Mango, and Banana, in India from 2012 to 2021. These figures suggest that India produces many fruits [2]. The fast speed of fruit production and the lack of skilled workers necessitate the implementation of an automated system inside the fruit industry. Once more, for sorting and packaging, the automation system may categorize fruits based on quality in accordance with market demand. The most essential aspect of fruits and vegetables is their appearance, which influences their market value and the preferences of consumers. Sorting and rating can be performed by humans, but it is unreliable, time-consuming, biassed, difficult, costly, and susceptible to environmental influences.

Therefore, an intelligent method for grading of fruit is required.

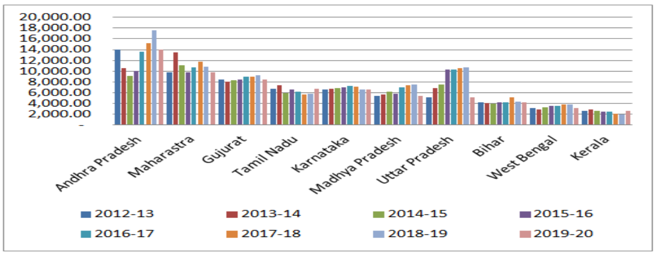

Figure 3. India's state-by-state production of fruits (in '000tonne) from 2012 to 2020 (@3rd advanced Estimate)

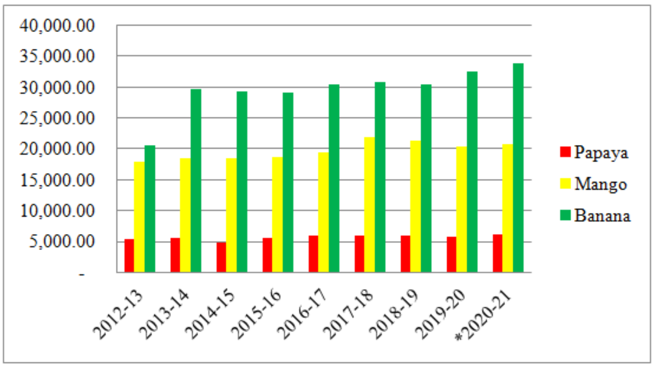

Figure 4. Production of three key fruits (@3rd advance estimate) from 2012 to 2021, in '000 tonne

Providing good-quality food to a person is a crucial task in the current mechanical era. It is possible to analyze the fruit quality; nonetheless, this review requires a lot of work. A programmed fruit-evaluating framework is required to complete this assignment for quality and sustenance. The structure of planned fruit reviews is also crucial. The non-destructive automatic quality method helps to discern the type of fruit without damaging. Owing to the poor technique, it might be challenging to determine the type of fruit based on its color, shape, and size. Computational expertise and machine learning techniques were used to pass this test, and the types of fruits were successfully identified. The number of farm workers in the fruit industry is steadily declining. Adopting labor-saving technology is crucial. The best method for fruit identification is image processing, which makes packaging and sorting easier. To determine the fruit's market worth, their size and quality must be quantified. Fruit quality inspection can only be performed manually by feeling and looking, which is impacted by numerous factors such as inconsistent and erratic decision-making. Consequently, image processing is the technology that works best for fruit identification and quantification [3].

This study uses machine learning and computational intelligence techniques to review the identification, classification, defect discrimination, and grading of three major fruits: Papaya, Mango & Banana. The remainder of this paper is organized as follows. The methods used for fruit identification, fruit classification according to variety, fruit grading, and defect detection in fruits according to quality are discussed in Sections 2, 3, 4, and 5, respectively. The review, prospects, and conclusions are presented in Sections 6 and 7.

2. FRUIT IDENTIFICATION

Numerous real-world situations have made use of fruit identification systems, including checkout lines at retail establishments, where they can replace hand scanner tags. It can also be used as a support system for the blind. Fruit identification in supermarkets is laborious, although the cashier must define the type of each item to determine its price. The best solution to this issue is a fruit and vegetable recognition system that automates the labelling and pricing calculations. Examples of several image-processing techniques employed by researchers working on autonomous fruit identification are presented in this paragraph.

A model using morphological features, such as area, major and minor axes, mean red and standard deviation, mean green and standard deviation, mean blue and standard deviation, mean hue and standard deviation, mean saturation and standard deviation, mean intensity, and mean saturation, was proposed by Mustafa et al. [4]. This recipe contained five fruit varieties: apples, bananas, mangoes, carrots, and oranges. Samples were collected using a digital camera. Fruits are classified using the Probabilistic Neural Network (PNN) classifiers are based on morphological and visual traits. The accuracy of the investigation was 90% with a seven-fold cross-validation. Based on the Fitness-Scaled Chaotic Artificial Bee Colony (FSCABC) algorithm and Feed-forward Neural Network (FNN), Zhang et al. [5] proposed a hybrid technique for classifying fruits. In total, 1653 images of 18 different fruit species were captured using a digital camera. The 256X256 pixel scaling sped up the process, but decreased the image quality. The images were captured in a rectangular window. A total of 64 color features, 8 form features, and 7 texture characteristics were extracted for each 256X256 pixel image. To preserve 95% of the original features, the feature dimension was reduced using Principal Component Analysis (PCA). A stratified five-fold cross-validation method was employed to enhance the capacity of the FNN to produce data. The accuracy of the proposed approach (89.1%) was higher than that of several other classifiers according to data. Lu et al. [6] presented a fruit categorization tool with the primary goal of quickly and precisely identifying fruits. The primary objective of this project was to categorize fruits using computer vision and artificial intelligence. To lower the misclassification rate, a single-hidden layer feed-forward neural network (SLFN) is proposed against the proposed classifier approach. Offline learning and prediction are the two phases of the proposed system. Images were obtained from the database and processed offline using PCA to preprocess, extract features, and reduce feature dimensions. The classifier received these properties, which were subsequently evaluated. The accuracy of the proposed methodology was 89.5%. When developing an object recognition control system, Khaing et al. [7] took convolutional neural networks (CNN) into account. This article explains the basic methodology for utilizing CNN in the control framework of the characterization process and the simulation findings. The system setup and validation used 971 images of the most well-liked fruit. These methods can be used to classify 30 different fruit varieties. There were approximately 32 different images for each fruit class. There were eight layers in the proposed CNN model. The loads and predispositions of each stratum were assessed according to a random sample. The maximum number of epochs was set to 1000; maximum learning rate, maximum learning decay rate, momentum, maximum weight decay rate, and early stopping patience were all set to 0, 0.005, 0.0001 and 50, respectively. They employed a predetermined learning arrangement in this instance. Because different fruit varieties are similar and external environmental changes, such as illumination, can affect their surroundings, automatic fruit recognition by machine vision is thought to be a difficult issue. Hussain et al. [8] proposed a novel Deep Convolution Neural Network-based fruit recognition system. They used 44406 images from 15 distinct categories as direct input to the DCNN for training and recognition in their experiment, without previously eliminating any features. The DCNN also acquired knowledge of the images' greatest qualities through an adaptation procedure. The proposed method automatically recognizes fruits with a high level of 99% accuracy. Al Haque et al. [9] proposed a CNN-based model to classify five different banana varieties, including cavendish, ladyfinger, sabri, green, and red bananas, and to identify which bananas are the most decaying. The second of the authors' two Deep Learning-based CNN models performed well, with a classification accuracy of 93.4±0.8% and rotten banana recognition accuracy of 98.3±0.8%. Bongulwar et al. [10] proposed a Model for the identification and classification of fruits using the concept of deep learning. The objective is to build an automatic system for feature extraction using convolutional neural networks. The proposed system uses high quality 'ImageNet' dataset. The dataset consists of five different categories of fruit images such as apple, banana, grape, litchi and mango etc. comprising of 4760 numbers of images. The dataset is divided into training and validation datasets in which 90% of the images are trained and 10% are validated. The model uses Convolutional Neural Networks to identify fruits from images. The accuracy obtained is 92.23%. Deep learning outperforms machine learning algorithms. To recognize bananas, Vijayalakshmi et al. [11] proposed a five-layer CNN with convolution, pooling, and fully connected layers. A CNN was used to extract features from fruits, including apples, strawberries, oranges, mangoes, and bananas. Various classification methods, such as Random Forest (RF) and K-nearest neighbor (KNN), have been used to identify fruits (KNN). The deep feature RF combination algorithms outperformed the existing systems by 96.98% when our Deep Learning-based RF and CNN methods were compared. Finally, a technique for configuring the advancement and control frameworks for vision-based automated basic leadership frameworks was developed (see Table 1 for more details).

Table 1. Various approaches used for fruit identification

References	Types of Fruits	Segmentation	Features	Classification	Accuracy(%)
[4]	Apples, Bananas, Mangoes, Carrots, and Oranges	N/A	Color and Geometrical feature	PNN	90%
[5]	Apples, Bananas, Plantains, Tangerines, Avocados, Watermelons, Cantaloupes, Pineapple, Pears	Split-and-Merge Algorithm	Texture and Shape feature	FNN	89.1%
[6]	Pineapples, Green plantains, Cantaloupes, Passion fruits, Tangerines, Apples, Pears, Grapes, Strawberries, Bananas, Berries, Watermelons	N/A	N/A	SLFN	89.5%
[7]	Apples, bananas, blueberries, kiwi fruits, Raspberries, etc.	N/A	N/A	CNN	94%
[8]	Apple, Banana, Mango, Orange, Peach, Pear, Tomatoes, Guavas, Kiwi, Persimmon, Papaya, Plum, Pomegranate, Ceram bola, Muskmelon, etc.	N/A	N/A	Resnet50 and DCNN	99%
[9]	Bananas	N/A	Texture and Shape feature	CNN	93.4 ± 0.8% 98.3 ± 0.8%
[10]	Apple, Banana, Grape, Litchi and Mango	N/A	Texture and Shape feature	CNN	92.23%
[11]	Apples, strawberries, oranges, mangoes, and bananas	N/A	N/A	CNN, Alexnet	96.98%

3. CLASSIFICATION FOR FRUITS

In computer vision, researchers worldwide have been paying close attention to classifying fruit images that are similar to or as accurate as human vision in recent years. Other than just considering the gesture of the fruit, such as color and size, many qualities of fruits are to be considered, such as genetic variation. Fruits should be categorized by variety; for instance, 15 different mango varieties, including Alphonso, Ambika, Amrapali, Banganpalli, Chausa, Dasheri, Himsagar, Kesar, Langra, Malgova, Mallika, Neelam, Raspuri, Totapuri, and Vanraj, are sold in supermarkets. Furthermore, no one is present to identify the specific variety of mangoes one buyer wants for a certain reason. Automated fruit variety recognition was a useful tool in this study. This automatic fruit variety recognition aids traders in grading fruit varieties according to customer satisfaction or appetite. In addition to grading, classification, and separation, it extends its compensation to scientists studying genetic variety and hybridization. This has brought about a greater revolution in the morphological features of the fruit kingdom. A detailed study on the classification of fruit varieties is presented in this section.

Five different types of fruit photographs have been rated by Savakar et al. [12]. Apple, Chickoo, Mango, Orange, and Sweet Lemon with 1000 shots of each fruit species or 5000 sample images overall were taken. This method concentrates on the textures and colors. This study considered 27 textures and 18 colors of the respective fruits. Color properties were determined by individually separating the RGB components. The components of the RGB image were then isolated and converted into an HSI model. The mean, variance, and range of each RGB and HSI component were calculated independently. Gray-level co-occurrence matrices (GLCM) were utilized to calculate the texture features. Apple, chickoo, mango, orange, and sweet lemon were classified at 93%, 94%, 92%, 92%, and 93%, respectively. Sahu et al. [13] developed automated software to identify and classify mango fruits according to their form, size, and colour traits using digital image analysis. Digital images of numerous mango fruits will be the starting point for pre-processing techniques that use morphological and texture analysis to build a binary picture. Subsequently, the images were further categorized using the best classification technique. The Image Processing Toolbox was used to identify and categorize fruits using MATLAB as the programming language. The proposed method can quickly and accurately classify mangoes by identifying their visual flaws, stems, sizes, and form. Rachmawati et al. [14] created a technique for the multi-class fruit recognition problem based on the hierarchical multi-feature classification (HMC) framework. HMC takes advantage of the benefits of fusing the fruit hierarchy property with multimodal characteristics. The benefit of using the color feature in the fruit recognition problem is that hybrid features may be formed by fusing it with the 3D shape feature of the depth component of the Red, Green, Blue, Depth images. When faced with a set of fruit species and variations that already have a hierarchy among them, we investigated the difficulty of assigning photos to one of these fruit types from a hierarchy-based perspective. According to previous reports, hybrid RGBD features in conjunction with a hierarchical structure can enhance classification performance. Mim et al. [15] presented a system for computerised image handling to classify Himsagar mangoes into six improvement phases in accordance with United States Department of Agriculture (USDA) standard gathering. The three main steps in the proposed system are assurance, preparation, and arrangement. Foundation subtraction also involves an extraction. Initially, they used the image division technique with global limit esteem to restrict the intraclass alteration of extremely distinguishing pixels. The second phase involved removing the highlights of mango pictures from the piecemeal image. The extracted highlights were then selected based on the relationship and information. In previous advancements, a choice tree was used to divide the images into six stages. The relationship-based property evaluator and the best-first pursuit were combined to identify the most fundamental highlights. Since they demonstrated relative changes across stages, H-mean, H-middle, H-LV, and I LV were chosen for grouping the highlights. Mazen and Nashat [16] suggest an automated computer vision method for banana maturity classification. First, a homemade database for the four classes was created. Second is an architecture based on an artificial neural network that considers hue, brown spot development, and Tamura. Statistical texture traits were used to categorize and rank the phases of banana fruit ripening. To assess the outcomes and consistency of the suggested model, naive Bayes, k-NN, decision tree, SVM, and discriminant analysis classifiers were utilized. This model is more accurate than other methods, with a 97.75% accuracy rate. Behera et al. [17] suggest two techniques for categorizing papaya maturity levels. Machine learning was the first method, followed by transfer learning. A total of 300 papaya fruit images were used in this experiment. Each ripeness level contained 100 unique papaya photos. Local Binary Pattern (LBP), Histogram of Directed Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), k-NN, SVM, and Naive Bayes are the traits and classification methods used in this model. Alexnet, Resnet101, Resnet50, Resnet18, VGG19, VGG16, and Googlenet are only a few of the seven pre-trained models used by Transfer Learning. While machine learning requires only 0.0995 s to train to obtain 100% accuracy, transfer learning takes longer. They increased the accuracy by 6% compared with the prior method. A new non-destructive multimodal classification method developed by Garillos-Manliguez and Chiang [18] are also presented. It assesses fruit ripeness by concatenating data from visible-light and hyperspectral imaging systems. This technique uses deep convolutional neural networks (CNNs). While RGB images of the sample fruits make it simple to assess morphological changes, hyperspectral images with a wavelength range of 400–900 nm can be used to create spectral fingerprints that are highly sensitive and correlate with the internal characteristics of fruits. These elements must be considered when creating a model. The Alexnet, VGG16, VGG19, Resnet50, Resnet50, Mobilenet, and MobilenetV2 designs were updated further in this work using multimodal data cubes made of RGB and hyperspectral data. These multimodal versions can categorize six phases with up to 0.90 F1 scores and a top-2 error rate of 1.45%. Deep learning algorithms that can be used to forecast fruit quality and maturity for fruit shelf life were proposed by Aherwadi et al. [19]. The second dataset, Fruit 360, was taken from Kaggle and contained 2100 images of banana fruit categorized as ripe, unripe, and over-ripe. To achieve a dataset size of up to 18,900, an image-augmentation technique was used. Both datasets were created using convolutional neural networks (CNN) and AlexNet techniques; the accuracies of the CNN and AlexNet models for the original dataset were 98.25% and 81.75%, respectively, while the accuracies for the enhanced dataset were 99.36% and 99.44%, respectively. Table 2 shows that the accuracies of the CNN and AlexNet models using the Fruit 360 dataset were 81.96% and 81.75%, respectively.

Table 2. Various approaches used for the classification of fruits

References	Fruit(s)	Segmentation	Features	Classification	Accuracy(In%)
[12]	Apple, Chickoo, Mango, Orange, and Sweet Lemon	N/A	Color and texture feature	BPNN	93%, 94%, 92%, 92%, and 93%
[13]	Mangoes	N/A	Shape, size & color feature	N/A	N/A
[14]	Apples, Bananas, Lemons, Limes, oranges, peaches, and pears	N/A	Colour, hybrid & 3D shape features	Hierarchical classification	N/A
[15]	Himsagar Mangoes	Global Threshold Values	Image feature	Decision tree	96%

[16]	Bananas	N/A	N/A	Naive Bayes, k-NN, decision tree, SVM, and discriminant analysis	97.75%
[17]	Papaya	N/A	N/A	LBP, HOG, GLCM, Naive Bayes, k-NN, SVM (in ML) and Alexnet, Resnet101, Resnet50, Resnet18, VGG-19, VGG-16, and Google-Net (In TL)	100%
[18]	Papaya	N/A	Colour & 3D shape features	MD-CNN	0.90 F1 scores and 1.45% top-2 error rate.
[19]	Bananas	N/A	N/A	CNN & Alexnet	98.25% & 81.75%, 99.36% & 99.44%, 81.96% & 81.75%

4. GRADING OF FRUITS

The fruit business has embraced an image processing approach. This is a quick, reliable, and objective inspection method. In recent years, fruit grading has become increasingly dependent on image processing. Grading entails categorizing fruits while considering disease severity, flaws, and contamination on the produce. Grading is a crucial phase of the postharvest procedure. However, manual fruit grading is a laborious and inaccurate process. Therefore, it is necessary to alter the automated speedier system. An automatic image-processing system is a dependable method for fruit sorting and grading. This section examines how image processing has evolved in the agricultural and food-processing sectors.

Razak et al. [20] used fuzzy analysis to propose autonomous mango grading. Color and skin features were collected using this scale. The area of the sample image was used to calculate mango size. Subsequently, the RGB component of the image was removed, and the average of the three-color components was determined. The edge detection approach was used for shape analysis. Mango was graded into different classes using fuzzy inference methods, which provided an overall accuracy of 80%. Zheng et al. [21] developed a mango rating system. The L*a*b* color model and fractal dimension were employed for grading. The fractal dimension and color accuracy obtained using SVM were 85.19% and 88.89%, respectively. Pandey et al. [22] proposed an automated mango grading technique that uses image processing. By applying the CIE Lab color model to extract color features, the Dominant Density Range approach divides mangoes into Healthy and Diseased groups. The color information of an object is efficiently represented using the L*a*b* color space. The color ratio determines mango health and sickness. After the discovery of healthy mangos, size-based grading was assessed using area and diameter. According to an experimental finding, the Dominant Density Range approach and the CIE Lab color model can be used to grade mangoes successfully. Mangoes can be classified into target classes with an average accuracy of 92.37% using the suggested approach. Nandi et al. [23] suggested an automatic prototype system for grading and sorting mangoes that makes use of fuzzy logic. Using a CCD camera set on top of a conveyor belt that is moving mangoes, the automated system collects video images. It then processes the images to gather pertinent attributes sensitive to mango size and maturity level. The Gaussian Mixture Model (GMM) was used to estimate the parameters of the various classes to forecast maturity. Mango fruits are automatically sorted and graded using fuzzy logic techniques, and the mango size is estimated from the binary image of the fruit. A new automated approach for sorting and grading mangoes based on computer vision algorithms is provided by Pauly and Sankar [24]. This method can be used to replace India's current manual sorting and grading process. Alphonso mango, a premium type of mango shipped from India, is the target market for the system. With an accuracy of 83.3%, the created system could sort Alphonso mangoes and recognize defective skin up to a minimum area of 6.09384510 -4 sqcm. Agilandeeswari et al. [25] suggested an autonomous multi-class support vector machine (SVM) based mango grading system. The mangoes were classified into three groups using a multi-class SVM classifier —very good, good, and bad—after pre-processing, segmentation, feature extraction, and classification. The proposed methodology has a 97% accuracy rate. Panda and Sethy [26] developed a system for Carica papaya grading using the Artificial Bee Colony algorithm (ABC) to classify papaya fruits from digital images. Our preliminary analysis of the image features suggests that the ABC algorithm's criteria for sorting papaya fruits into different grades could include impacted area, shape, and texture. Fuzzy logic, naive Bayes classifier, and support vector machine (SVM) are evaluated for their effectiveness in rating papayas. The input papaya was divided into two groups during the classification process: healthy and defective. The SVM classifier provides an accuracy of 93.5% in all grading steps, the naive Bayes classifier provides an accuracy of 92%, and fuzzy logic provides an accuracy of 86.04%. The accuracy of the proposed optimization techniques for various papaya fruit picture databases is 94.04%. Naik [27] proposed two techniques for mango fruit grading. The CNN was initially trained using mango samples divided into classes I, II, III, and IV. In comparison, the second method used three stages for mango grading. The CNN is trained using labels for the shape parameter in the first phase, which are both well-formed and deformed; labels for the size parameter in the second phase, which are small, medium, and large; and labels for the maturity parameter in the third phase, which are ripe, partially ripe, and unripe. These three processes are used to base the grade decision. Ucat and Dela Cruz [28] presented a post-harvest grading categorization of Cavendish bananas using deep learning and TensorFlow. Python OpenCV and TensorFlow were employed to create an algorithm and increase classification accuracy. The number of bananas utilized was 1116, and there were 279 images in each of the three categories (cluster Class A (part of hand), class A big-hand or small-hand, and Class B big-hand or small-hand). Four procedures are used for the sample images: picture thresholding, feature extraction, classification prediction, and testing. Regarding the expected accuracy across all classes, the extraction of the finger size value (small or large hand) was more significant than the extraction of the surface defect value (A and B). In all four classes across all trained validation and test data, the final classification displayed accuracy above 90%. Based on maturity, size, form, and flaws, Supekar and Wakode [29] presented a novel approach to evaluate Dashehari mangoes. 85 Dashehari mangoes were compiled into a dataset. Mangoes were viewed from two angles, making the devised technique more dependable. Before determining the mango grade, each grading parameter category for mangoes was established (grades 1, 2, 3, and 4). The random forest classifier accomplished perfect categorization based on ripeness and form. However, several medium and small mangoes have been incorrectly classified based on their size. The accuracy of the test set classification based on ripeness, size, and form was 100%, 98.19%, and 99.20%, respectively. The segmentation method based on K-means clustering also yielded good results in locating mango flaws. The mango grade was determined using a formula for mango grading. Sixteen of the 18 test mangoes were correctly assessed, resulting in a grading accuracy of 88.88%. Therefore, mango grading, image processing, and machine-learning approaches have been successfully used. This technique can be used for other mango types in future studies. Firmness and sweetness are the two other grading standards that can be used. Creating a multi-variant grading system that determines the mango variety before carrying out the proper grading is possible. Four groups were created by Raghavendra et al. [30] to categorize mangoes according to their level of ripeness. The work was tested by conducting lengthy experiments on a recently developed group of 981 images of the Alphonso mango variety, categorized into four categories: under-ripe, perfectly ripe, overripe with internal issues, and overripe without internal abnormalities. Mangoes were divided into four classes using a hierarchical technique. At each level of classification, the characteristics from the L*a*b color space were extracted. Various classifiers and their potential combinations were tested for classification at each level. The study discovered that when categorizing mangoes into under-ripe, perfectly ripe, and over-ripe, the thresholding classifier outperforms the Support Vector Machine (SVM) classifier in classifying over-ripe with internal faults and over-ripe without internal defects. Furthermore, a traditional single-shot multiclass classification strategy using SVM was tested to highlight the advantages of the hierarchical approach. The results of the experiment revealed that several modern models and the matching conventional single-shot multi-class classification strategy outperformed the hierarchical method, with an accuracy of 88%. Mesa and Chiang [31] suggested a non-invasive automated banana grading system that uses deep learning methods, RGB, and hyper spectral imaging. In accordance with international rules, a real dataset of pre-classified banana tiers (Class 1 for export-quality bananas, Class 2 for the local market, and Class 3 for faulty fruits) was used. Fewer samples were used with the multi-input model than with earlier methods in the literature, and the results showed an excellent overall accuracy of 98.45%. Gururaj et al. [32] provided a system of grading mangoes that is intelligent and can determine the overall quality of the fruit based on its appearance, such as maturity ripening stage, shape, color, texture, and fault features, among others. The efficiency of the proposed system was improved by the characteristics of the CNN, which had 93.23% accuracy for variety recognition, and 95.11% accuracy for quality grading. The automatic mango sorting and grading model that Iqbal and Hakim [33] reported using a DL technique considered eight categories of harvested mango qualities, such as shape, size, color, and texture. Image rotation, translation, zooming, sharing, and horizontal flipping were accomplished using data augmentation techniques. The Inception v3 CNN architecture achieved 99.2% sorting accuracy and an average grading accuracy of 96.7% when compared to the VGG16, ResNet152, and Inception v3 techniques while using supplemented data. A low-cost machine vision system based on deep learning was proposed by Ismail and Malik [34] to grade fruits according to their external appearance or freshness. The system was trained and assessed (apples and bananas) on two datasets. Using the EfficientNet model, the average accuracies for the test sets for apples and bananas were 99.2% and 98.6%, respectively. While using stacking ensemble deep learning approaches, they also found a minor increase in the recognition rate of 0.03% for apples and 0.06% for bananas. It was discovered that the new approach outperformed earlier methods used on identical datasets. Furthermore, real-time testing of actual samples revealed that the accuracy was 96.7% for apples and 93.8% for bananas, demonstrating the effectiveness of the proposed system, as displayed in Table 3.

Table 3. Various techniques applied for grading fruits

References	Types of Fruits	Segmentation	Features	Classification	Accuracy (in%)
[20]	Mangoes	N/A	N/A	Fuzzy classification	N/A
[21]	Mangoes	N/A	Fractal Dimension (FD) and L*a*b* values	Least-Squares Support Vector Machine (LS-SVM)	85.19% and 88.89%
[23]	Mangoes	N/A	size and maturity	Fuzzy Logic technique	N/A
[24]	Mangoes	N/A	shape & size	OpenCv2 and python2.7	83.30%
[25]	Mangoes	thresholding	Geometrical, texture, and statistical	SVM	97%
[26]	Papayas	K-Mean clustering	shape, texture, and defects	ABC	94.40%
[27]	Mangoes	N/A	shape, size, and maturity	SVM	N/A
[28]	Bananas	thresholding	defects and size	CNN	93%
[29]	Mangoes	K-Mean clustering	ripeness, size, and shape	random forest classifiers	89%
[30]	Mangoes	N/A	shape, size, and defects	CNN	88%
[31]	Bananas	N/A	size and texture	CNN	98%

[32]	Mangoes	N/A	shape, color, texture, and defect	CNN	93.23% and 95.11%
[33]	Mangoes	N/A	size, shape, color, and texture	CNN	99.2% and 96.7%
[34]	Apples and bananas	Mean shift clustering and Watershed	shape & size	CNN	96.7% and 93.8%

5. DEFECT DETECTION ON FRUITS

Quality evaluation is one of the most crucial elements in enhancing the marketability and waste management of agricultural goods. New, non-destructive techniques called image processing systems have a variety of uses in the agricultural industry, including product grading. Defects are one of the most frequent causes of loss of fruit quality in the fruit industry. In recent years, skin damage and odor classification have become the basis for fault development. For instance, rust, a fungal disease caused by pathogenic fungi in fruits, is costly for farmers a lot of money. Therefore, modern fruit stores are interested in advancements in various technologies that differentiate fruits in terms of colors, sizes, and faults, and boost separation and classification efficiency.

Rivera et al. [35] developed an HSI system for the early detection of mechanical damage caused in mango fruit. They used a variety of classification learning algorithms and selected the best spectral bands to distinguish between damaged and sound mangos to obtain increasing rates of classification correctness over the course of seven days following damage induction. Naive Bayes, ELM, DT, LDA, and k-NN, the classifiers employed on day one, each attained rates of 67.46, 84.63, 89.27, 89.76, and 94.87, respectively. These were sufficiently high by day three (97.5% and 95.54%, respectively), followed by LDA, and had the best overall classification result. It is important to note that feature selection resulted in inferior classification performance compared with the entire spectral bandwidth. Hence, an additional study is advised to obtain a more effective feature selection. To categorize the evident mango flaws, feature extraction approaches have been proposed by Ashok and Vinod [36]. The "Alphonso" mango was acquired using 1766 colour pictures of varying quality levels. A sequential forward selection technique was used, and nine different combinations of textural features were considered, with the most pertinent aspects being chosen from each case. Designing neural networks (NN) with cross-validated performance accuracy of 90.09% for linear, 90.26% for logistic, and 90.26% for softmax activation functions was made easier by the generalized linear model classifier. Textural features such as statistics, LBP, and filter banks are also useful in this process. Patel et al. [37] have proposed a development methodology of color computer vision to identify two market types (Chausa and Dashehari) of Indian mangoes. Images of the fruits of both cultivars were first taken with a color (RGB) camera and the proper lighting arrangement to avoid highlights and light reflection. Second, LabVIEW software created an algorithm for pre-processing to segment mangoes' outward flaws. After image processing and faulty particle filtering, the number of pixels whose gray level was found to be lower than the threshold value during particle analysis was counted. The effectiveness of the algorithm was also assessed in terms of the precision, effectiveness, and time required to process and examine the image. The proposed algorithm was 88.6% accurate and 93.3% effective. As the degree of faults on the mango fruit surface increased, the average inspection duration increased. A machine-vision-based agro-medical expert system was proposed by Habib et al. [38] identified papaya disease. Papaya color image samples of size 128 were considered, both with and without error. The disease-attacked region was segmented from the acquired image using the K-means clustering algorithm, and the necessary characteristics were then retrieved. Using a support vector machine, the diseases were classified with an accuracy of 90.15 percent. Raghavendra et al. [39] suggested wavelength selection techniques to determine the range of wavelengths for classifying defective and fruitful mangoes. In this study, feature-selection techniques were used to select several wavelengths. The dataset was gathered using (NIRnear-infrared) spectroscopy to evaluate the model's effectiveness, with wavelengths ranging from 673 to 1900 nm. Euclidean distance measurements were used for classification in both the original feature space and Fisher's Linear Discriminant (FLD) modified space. The experimental findings demonstrated that the most effective wavelength for detecting internal mango flaws is in the lower range (673 nm-1100 nm). The most effective way to distinguish unhealthy and defective mango fruits using wavelength selection appears to be Fisher's criterion-based strategy. This was discovered as part of an investigation of different feature selection techniques to further express the effectiveness of the model. The best wavelengths were discovered using Fisher's criterion, with 84.5% of classification accuracy, in the range of 702.72 nm to 752.34 nm. Deep learning approach is also applied to detection of leaf diseases [40].

6. REVIEW AND PROSPECT

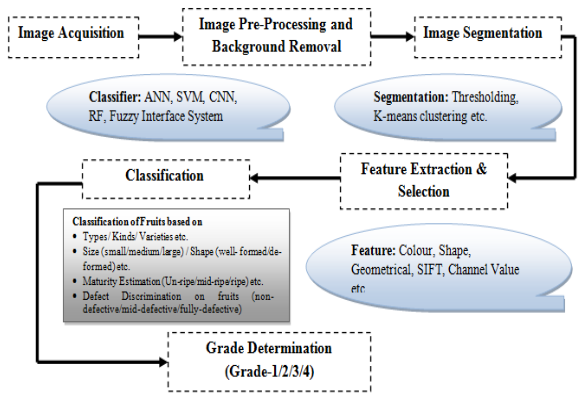

Figure 5. A generally acceptable processes for fruit recognition

Applying image processing methods will ultimately improve the qualitative and quantitative evaluation of fruit and vegetable recognition, categorization, and disease detection in fruits and vegetables among local goods in agricultural regions. The advantages of this vision-based technology include speed, persistence, and non-destructiveness. These obstacles include poor lighting and a variety of capture sites, whereas variability, cropping, and osculation do not affect the ability to distinguish various types of fruits. The survey found that most researchers who study fruit inspection and/or analysis follow the same methodology, as shown in Figure 5. There are some research challenges and limitations that can improve the current state-of-the-art.

6.1 Challenges

- Reduced effort, labor costs, and other expenses are benefits of employing computer vision in fruits and vegetables. The conventional method requires sufficient time to process defects, whereas computer vision automatically reduces the processing time for defect identification.
- Fruit and vegetable databases are more challenging for classification and identification because of their unique size, shape, color, and defects.
- Flaw detection can be achieved using various datasets of fruit components. For example, a training model can be built using a width multiplier, and checking can be performed at a faster rate.

6.2 Limitations

- Existing computer vision techniques require the creation of a dataset; however, they consume more time. This is one of the main disadvantages of the proposed method.
- Another disadvantage is that if the processing time to process an image is longer, it may lead to a vacillation effect.
- Fruits are more environment-dependent, which is a significant drawback because the same computer vision technique may result in variable degrees of accuracy in the dataset.
- Sometimes, the accuracy can be improved by improper exploration of the internal fruit structures, which increases the likelihood of finding flaws and performing quality analysis.
- It is necessary to be more trustworthy and efficient in creating new algorithms and techniques for data extraction, processing, and analysis.
- The present feature extraction methods cannot extract spectral data from different regions of the fruit. Therefore, it is necessary to create a multichannel spectroscopic system that can instantly check for internal faults in various fruits.
- To further develop this (neural network) approach as a technical framework that might be used for a variety of industrial applications, such as the identification of fruit and vegetable quality deficiencies.

7. CONCLUSION

Recent, high-quality studies on fruit identification and grading were the primary focus of this investigation. The researcher may collect information on pre-processing, segmentation, feature extraction, feature selection, and classification strategies for fruit identification with the use of this survey. Several problems with fruit identification were analysed, the difficulties were detailed, and a solution that seems to work well in most cases was proposed. Image processing is useful in the fruit industry because it allows for assessments to be made rapidly, cheaply, hygienically, consistently, and objectively. Real-time systems are not available to the general public even if adequate accuracy and efficiency in the algorithms have been developed. It's possible that researchers in this area would be keen to work on such systems. Further, this paper provide the idea and information about the adapted methodolgies used for fruit classification, grading and quality inspection with their advantages and limitations.

REFERENCES

[1] Horticulture database APEDA Ministry of Commerce and Industries, Government of India. https://apeda.gov.in/apedawebsite/six_head_product/FFV.htm.

[2] Sharma, S., Sharma, A. (2021). Trends in production and export of major fruits in India. Indian Journal of Economics and Development, 17(2): 462-467. http://dx.doi.org/10.35716/IJED/20282

[3] Vijaya, K., Arun, C. (2017). Automated risk identification using NLP in cloud-based development environments. Journal of Ambient Intelligence and Humanized Computing. https://doi.org/10. 1007/s12652-017-0503-7

[4] Mustafa, N.B.A., Arumugam, K., Ahmed, S.K., Sharrif, Z.A.M. (2011). Classification of fruits using Probabilistic Neural Networks- Improvement using color features. 2011 IEEE conference on TENCON, Bali, Indonesia, pp. 264-269. https://doi.org/10.1109/TENCON.2011.6129105

[5] Zhang, Y., Wang, S., Ji, G., Phillips, P. (2014). Fruit classification using computer vision and feed-forward neural network. Journal of Food Engineering, 143: 167-177. https://doi.org/10.1016/j.jfoodeng. 2014.07.001

[6] Lu, S., Lu, Z., Phillips, P., Wang, S., Wu, J., Zhang, Y. (2016). Fruit classification by HPA-SLFN. In 2016 IEEE Conference on Wireless Communications & Signal Processing, Yangzhou, China, pp. 1-5. https://doi.org/10.1109/ WCSP. 2016.7752639

[7] Khaing, Z.M., Naung, Y., Htut, P.H. (2018) Development of control system for fruit classification based on convolutional neural network. In 2018 IEEE Conference on Russian Young Researchers in Electrical and Electronic Engineering, Moscow and St. Petersburg, Russia, pp. 1805-1807. https://doi.org/10.1109/EIConRus.2018.8317456

[8] Hussain, I., He, Q., Chen, Z. (2018). Automatic fruit recognition based on DCNN for commercial source trace system. International Journal on Computational Science & Applications (IJCSA), 8(2/3): 01-14. https://doi.org/10.5121/ijcsa.2018.8301

[9] Al Haque, A.S.M.F., Hakim, M.A., Hafiz, R. (2021). CNN-based automatic computer vision system for strain detection and quality identification of banana. 2021 International Conference on Automation, Control, and Mechatronics for Industry 4.0 (ACMI), Rajshahi, Bangladesh, pp. 1-6. IEEE. https://doi.org/10.1109/ACMI53878.2021.9528269

[10] Bongulwar, D.M. (2021). Identification of fruits using deep learning approach. IOP Conference Series: Materials Science and Engineering, 1049(1): 012004. https://doi.org/10.1088/1757-899X/1049/1/012004

[11] Vijayalakshmi, M., Peter, V.J. (2021). CNN-based approach for identifying banana species from fruits. International Journal of Information Technology, 13(5): 27-32. http://dx.doi.org/10.1007/s41870-020-00554-1
[12] Savakar, D. (2012). Identification and classification of bulk fruits images using artificial neural networks. International Journal of Engineering and Innovative Technology (IJEIT), 1(3): 35-40.
[13] Sahu, D., Dewangan, C. (2017). Identification and classification of mango fruits using image processing. IJSRCSEIT, 2(2): 203-210.
[14] Rachmawati, E., Supriana, I., Khodra, M.L. (2017). Toward a new approach in fruit recognition using hybrid RGBD features and fruit hierarchy property. In 2017 IEEE Conference on Electrical Engineering and Computer Science Informatics, Yogyakarta, Indonesia, pp. 1-6. https://doi. org/10.1109/EECSI.2017.8239110
[15] Mim, F.S., Galib, S.M., Hasan, M.F., Jerin, S.A. (2018). Automatic detection of mango ripening stages–An application of information technology to botany. Scientia Horticulturae, 237: 156-163. https://doi.org/10.1016/j.scienta.2018.03.057
[16] Mazen, M.A.F., Nashat, A.A. (2019). Ripeness classification of bananas using an artificial neural network. Arabian Journal for Science and Engineering, 44(8): 6901-6910. https://doi.org/10.1007/s13369-018-03695-5.
[17] Behera, S.K., Rath, A.K., Sethy, P.K. (2020). Maturity status classification of papaya fruits based on machine learning and transfer learning approach. Information Processing in Agriculture, 8(2): 244-250. https://doi.org/10.1016/j.inpa.2020.05.003
[18] Garillos-Manliguez, C.A., Chiang, J.Y. (2021). Multimodal deep learning and visible-light and hyperspectral imaging for fruit maturity estimation. Sensors, 21(4): 1288. https://doi.org/10.3390/s21041288
[19] Aherwadi, N., Mittal, U., Singla, J., Jhanjhi, N.Z., Yassine, A., Hossain, M.S. (2022). Prediction of fruit maturity, quality, and its life using deep learning algorithms. Electronics, 11(24): 4100. https://doi.org/10.3390/electronics11244100
[20] Razak, T.R.B., Othman, M.B., Bakar, M.N.A., Ahmed, K.A., Mansor, A.R. (2012). Mango grading using fuzzy image analysis. In International Conference on Agricultural, Environment and Biological Sciences (ICAEBS), Phuket, Thailand.
[21] Zheng, H., Lu, H. (2012). A least-squares support vector machine (LS-SVM) based on fractal analysis and CIELab parameters for the detection of browning degree on mango. Computers and Electronics in Agriculture, 83: pp. 47-51. https://doi.org/10.1016/j.compag.2012.01.012
[22] Pandey, R., Gamit, N., Naik, S. (2014). Non-destructive quality grading of mango (Mangifera Indica L) based on CIELab colour model and size. In IEEE International Conference on Advanced Communications, Control, and Computing Technologies. https://doi.org/10.1109/ICACCCT.2014.7019298
[23] Nandi, C.S., Tudu, B., Koley, C. (2014). Machine vision based techniques for automatic mango fruit sorting and grading based on maturity level and size. In Sensing Technology: Current Status and Future Trends 11, pp. 27-46. https://doi.org/10.1007/978-3-319-02315-1_2
[24] Pauly, L., Sankar, D. (2015). A new method for sorting and grading of mangos based on computer vision system. In 2015 IEEE International Advance Computing Conference (IACC), Banglore, India, pp. 1191-1195. https://doi.org/10.1109/IADCC.2015.7154891
[25] Agilandeeswari, L., Prabukumar, M., Goel, S. (2017). Automatic grading system for mangoes using multi-class SVM classifier. International Journal of Pure and Applied Mathematics, 116(23): 515-523.
[26] Panda, S., Sethy, P.K. (2017). Post-harvest grading for Carica Papaya fruit using image segmentation and soft computing. International Journal for Advance Research in Computer Science, 8. https://doi.org/10.26483/ijarcs.v8i7.4381
[27] Naik, S. (2019). Non-destructive mango (Mangifera Indica L., cv. Kesar) grading using convolutional neural network and Support Vector Machine. In International Conference on Sustainable Computing in Science, Technology & Management (SUSCOM-2019), pp. 670-678. https://dx.doi.org/10.2139/ssrn.3354473.
[28] Ucat, R.C., Dela Cruz, J.C. (2019). Post-harvest grading classification of Cavendish banana using deep learning and TensorFlow. In Proceedings of the International Symposium on Multimedia and Communication Technology (ISMAC), Philippines, pp. 1-6. https://doi.org/10.1109/ISMAC.2019.8836129.
[29] Supekar, A.D., Wakode, M. (2020). Multi-parameter based mango grading using image processing and machine learning techniques. INFOCOMP Journal of Computer Science, 19(2): 175-187. https://doi.org/10.18568/ijcs.19.2.2233
[30] Raghavendra, A., Guru, D.S., Rao, M.K., Sumithra, R. (2020). Hierarchical approach for ripeness grading of mangoes. Artificial Intelligence in Agriculture, 4: 243-252. https://doi.org/10.1016/j.aiia.2020.10.003
[31] Mesa, A.R., Chiang, J.Y. (2021). Multi-input deep learning model with rgb and hyperspectral imaging for banana grading. Agriculture, 11: 687. https://doi.org/10.3390/agriculture11080687
[32] Gururaj, N., Vinod, V., Vijayakumar, K. (2022). Deep grading of mangoes using convolutional neural network and Computer Vision. Multimedia Tools and Applications, 1-26. https://doi.org/10.1007/s11042-021-11616-2
[33] Iqbal, H.M.R., Hakim, A. (2022). Classification and grading of harvested mangoes using convolutional neural network. International Journal of Fruit Science, 22(1): 95-109. https://doi.org/10.1080/15538362.2021.2023069
[34] Ismail, N., Malik, O.A. (2022). Real-time visual inspection system for grading fruits using computer vision and deep learning techniques. Information Processing in Agriculture, 9(1): 24-37. https://doi.org/10.1016/j.inpa.2021.01.005
[35] Rivera, N.V., Gómez-Sanchis, J., Chanona-Pérez, J., Carrasco, J.J., Millán-Giraldo, M., Lorente, D., Cubero, S., Blasco, J. (2014). Early detection of mechanical damage in mango using NIR hyperspectral images and machine learning. Biosystems Engineering, 122: 91-98. https://doi.org/10.1016/j.biosystemseng.2014.03.009
[36] Ashok, V., Vinod, D. S. (2016). A comparative study of feature extraction methods in defect classification of mangoes using neural network. In Second International Conference on Cognitive Computing and Information Processing (CCIP). https://doi.org/10.1109/CCIP.2016.7802873

[37] Patel, K.K., Kar, A., Khan, M.M. (2019). Common external defect detection of mangoes using color computer vision. Journal of The Institution of Engineers (India): Series A, 100: 559-568. https://doi.org/10.1007/S40030-019-00396-6

[38] Habib, M.T., Majumder, A., Jakaria, A.Z.M., Akter, M., Uddin, M.S., Ahmed, F. (2020). Machine vision based papaya disease recognition. Journal of King Saud University-Computer and Information Sciences, 32(3): 300-309. https://doi.org/10.1016/j.jksuci.2018.06.006

[39] Raghavendra, A., Guru, D.S., Rao, M.K. (2021). Mango internal defect detection based on optimal wavelength selection method using NIR spectroscopy. Artificial Intelligence in Agriculture, 5: 43-51. https://doi.org/10.1016/j.aiia.2021.01.005

[40] Huang, Y.L., Li, N., Liu, Z.B. (2023). An enhanced convolutional neural network for accurate classification of grape leaf diseases. Information Dynamics and Applications, 2(1): 8-18. https://doi.org/10.56578/ida020102