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Fruits and vegetables quality evaluation using computer vision: A review

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A R T I C L E I N F O

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A B S T R A C T

In agriculture science, automation increases the quality, economic growth and productivity of the country. The export market and quality evaluation are affected by assorting of fruits and vegetables. The crucial sensory characteristic of fruits and vegetables is appearance that impacts their market value, the consumer's preference and choice. Although, the sorting and grading can be done by human but it is inconsistent, time consuming, variable, subjective, onerous, expensive and easily influenced by surrounding. Hence, an astute fruit grading system is needed. In recent years, various algorithms for sorting and grading are done by various researchers using computer vision. This paper presents a detailed overview of various methods i.e. preprocessing, segmentation, feature extraction, classification which addressed fruits and vegetables quality based on color, texture, size, shape and defects. In this paper, a critical comparison of different algorithm proposed by researchers for quality inspection of fruits and vegetables has been carried out.

Contents

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1. Introduction

In representing the conception for human brain, images are the most basic method in physical classification of foodstuff and agricultural industry. Factors affecting fruits and vegetables can be quantified visually which is laborious, expensive and is easily effected by physical factors, including inconsistent evaluation

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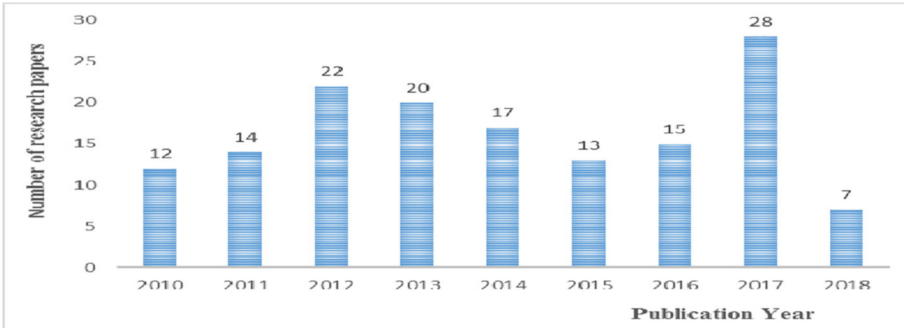

Fig. 1. Year wise number of research papers published in this field.

and subjective results. The market prices are determined by such inspections and, also, the "best-if-used-before date". The trained human investigators have done the quality inspection by feeling and seeing. This method is significantly inconsistent, fickle and decisions are seldom same among investigators. In this type of environment, the analysis of fruits and vegetables for several aspect criterions is a continual task; machine vision systems are best befitted for conventional analysis and quality assurance. In agriculture, computer vision system and image processing is readily growing research area which is a significant analyzing technique for pre to post harvesting of crops. Fig. 1 shows the number of research papers published year wise (to the best of our knowledge). From this graph, it can be easily seen the trend in this research field.

The data and information in agriculture mainly originates from photographic images but mathematically to estimate or process photographic data, it is challenging. Therefore, digital image processing technology helps to process images and attempt an extension for their analysis. Image processing has various applications in the field of agricultural like identification of land (Erdenee et al., 2010), evaluation of nitrogen recognition plant (Tewari et al., 2013), recognition of pest infected areas (Krishna and Jabert, 2013), automatic classification and detection of plant disease from shape, texture and color (Patil and Kumar, 2011). As, information science is rapidly growing, computer vision based pattern recognition and image processing are matured technique for safety and quality analysis of several agricultural applications. Computer vision technology corresponds the effect of the human vision in inspecting quality of fruits and vegetables by electronically perceiving an image, interpret and recognize the characters and an information is provided for the quality grading and sorting machine. Various research papers have been published (Naik and Patel, 2017a; Dubey and Jalal, 2015a; Zhang et al., 2014a), some of them focus on particular fruit in quality analysis while others are centered on particular techniques. A detailed summarization of quality analysis of fruits and vegetables is not available. Thus, the objective of this review paper is to give comparable survey of computer vision and image processing techniques in the food industry and also to review various segmentation, image features and image descriptors in the literature and quality analysis of fruits and vegetables on the basis of color, shape, size and texture and the type of disease present. Also, the principal components, basic theories and corresponding analysis and processing methods are reported.

2. Fruits and vegetables quality inspection

Quality inspection of fruits and vegetables using image processing technique involves five steps, as depicted in Fig. 2, namely, image acquisition, pre-processing, image segmentation, feature extraction and classification.

2.1. Image acquisition

In food applications, image acquisition tools used are camera, ultrasound, magnetic resonance imaging (MRI), and electrical tomography and computed tomography (CT). To generate the digital image charged coupled device (CCD) and complementary metal oxide semiconductor (CMOS) image sensors are used. A typical computer vision system inhere (Fig. 3) five fundamental components: illumination, an image capture board (digitizer or frame grabber), a camera, and computer hardware. In the analysis of fruits and vegetables, the light systems are structured as front and back lighting. To inspect the surface quality attributes like color, texture and skin defects front lighting is defined. However, to inspect the boundary quality attributes like size and shape back lighting is defined. The traditional, multispectral and hyperspectral computer vision systems are defined extensively for the quality analysis of food and agricultural products.

2.1.1. Computer vision system

In the late 1960s traditional computer vision system began which is now extensively used in aerospace field, industrial automation, security inspections, intelligent transportation system, medical imaging military utilization, robot guidance, autonomous vehicle, food quality and safety inspection, etc. As the traditional computer vision system accounts primary colors: red, green, blue (RGB), so the images acquired by RGB color cameras are centered at RGB wavelength. By using computer vision system, many characteristics like texture, shape, color, size and defects can be graded and inspected automatically. But some defects due to texture and color is identical to skin which is a challenging task to detect. Hyperspectral computer vision system (Lorente et al., 2012) combines both spectroscopic and imaging techniques which provide spectral information for each pixel of the spatial image. "The data structure of hyperspectral image is commonly called hypercube or data cube and can be viewed as a set of spectrums

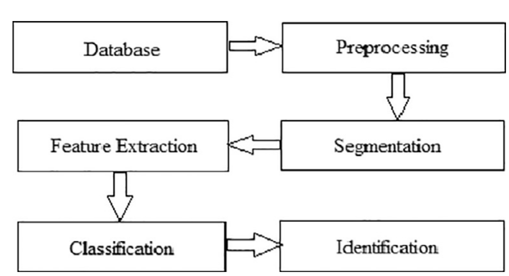

Fig. 2. A generlized block diagram of identication in image processing.

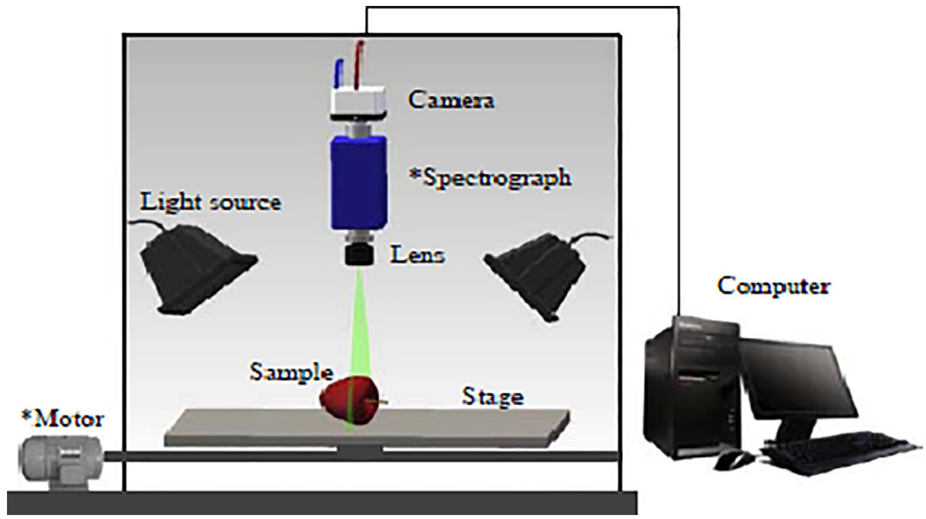

Fig. 3. A classical computer vision system (Zhang et al., 2014a).

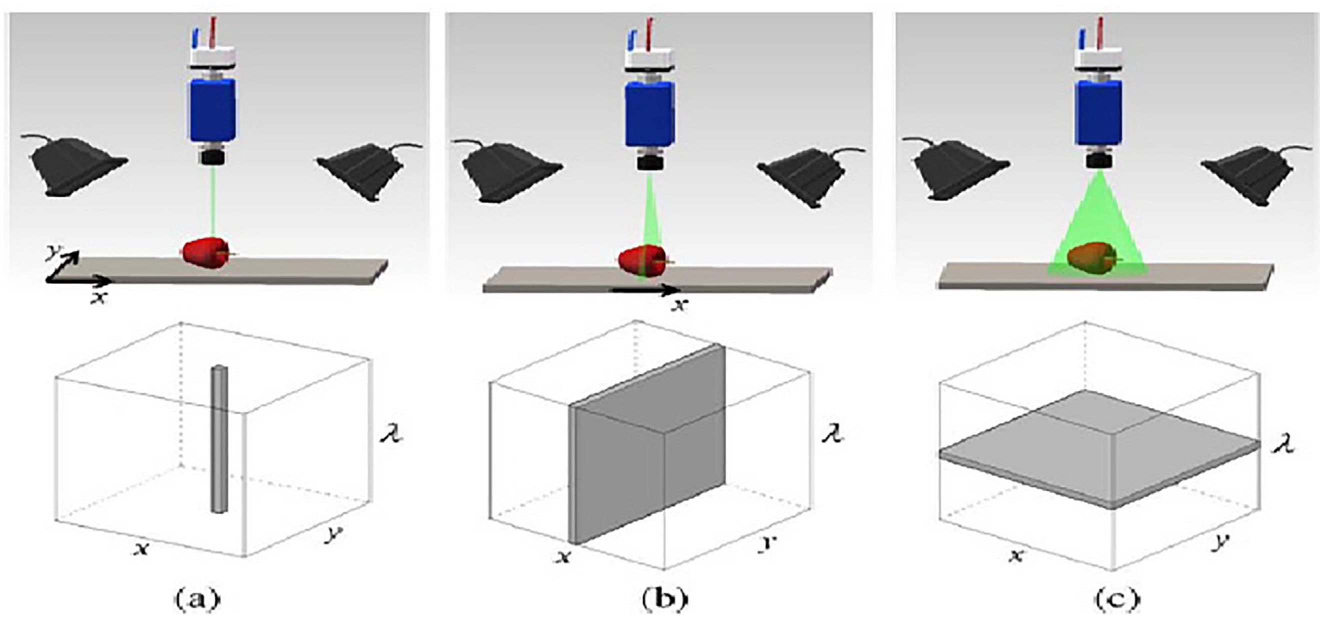

Fig. 4. Hyperspectral image scanning mode (a) Point scanning (b) Line scanning (c) Area scanning (Zhang et al., 2014a).

of each pixel in one two-dimensional image cluster together". The methods which are commonly used to achieve the hyperspectral image cube are point scanning, line scanning and area scanning which are illustrated in Fig. 4. In multispectral computer vision system, the monochromatic image of two or more waveband are captured.

2.1.2. Ultrasound and infrared

Initially, for grading the content of moisture in food products ultrasound has been used; conclude the intrinsic fat of bovine; and evaluating and studying the hydration and turgidity of the orange peel. When ultrasound and computer vision system are fall to produce desired image much longer wavelength are used for image acquisition. Infrared range (IR) lies from "700 to 1000 nm", and the approach generating infrared range is known as thermographic photography. "Thermographic imaging is based on the principle that all objects emit a certain amount of thermal radiation as a function of their temperature".

2.1.3. Tomographic imaging

When scientists need to observe the internal aspect of sample, tomography is used. It comprises of nuclear energy of substantial attribute for illustrating the two-dimensional distribution of object, from a sequence of one-dimensional projections and to generate the projection data sources are scanned. This method is done over multifold viewing angles as far as the prescribed set of all projection data are achieved. The applications are evolved to real-time monitoring as foods are processed, stored, packaged, and distributed.

Images acquired by different researcher using computer vision system consist of following characteristic as shown in Table 1.

2.2. Preprocessing

Images acquired by various types of techniques consist of multiple noises which deteriorate the aspect of an image. Therefore, it cannot contribute appropriate data for image processing. The

Table 1
Characteristics of dataset acquired by different researchers.

Author(s)	Fruit	Camera	Number of Images	Resolution (mm/pixel)	Size (Pixels)
Blasco et al. (2003)	Apple (Royal Gala)	EDS, 550D, Canon Inc., Japan	96	0.03	3456 × 2304
	Mango	EDS, 550D, Canon Inc., Japan	100	0.03	5184 × 3456
	Orange	EDS, 550D, Canon Inc., Japan	125	0.06	2592 × 1728
	Golden Apple	EDS, 550D, Canon Inc., Japan	100	0.03	3456 × 2304
	Apple Royal (Multispectral)	JAI AD-130 GE	98	0.128	1296 × 966
Rong et al. (2017)	Oranges (Jiangxi Navel Orange)	CCD Camera Pumix TMC-7DSP	1191	0.28	640 × 480
Naik and Patel (2017)	Mango	Thermal Camera FLIR ONE	250	–	240 × 320
Pereira et al. (2018)	Golden Papaya	Sony, Japan		–	–
Si et al. (2017)	Potato	Canon power shot SX260 HS	57	–	–
Jhawar (2016)	Orange	DSC 2000 Sony Camera	160	–	640 × 480
Prabha and Kumar (2013)	Banana	Olympus SP-510 UZ	120	–	3072 × 2304

preprocessing enhance the image data, which overcome reluctant distortions and enlarge the features of image that are essential for processing and build a relevant image (degraded form) than the original for a definite application. The approaches used for an image pre-processing for food quality assessment are pixel pre-processing and local pre-processing. Pixel preprocessing "converts an input image into an output image such that each output pixel is correlated to the input pixel having the corresponding coordinates". The uttermost frequent method for pixel pre-processing is color space transformation (CST) for assessment of food quality. Most of the CST applications depends on hue, saturation and intensity (HSI) color space in which saturation results in monochromatic image, impart the meat image texture vividly. Local pre-processing (Filtration) "use a small neighborhood of a pixel in an input image to produce a new brightness value in the output image". It uses simple filter (reduce noise), median filter (reduce peak noise) and modified unsharped filter (to identify cracks in egg).

2.3. Segmentation

After preprocessing, image segmentation is required which separates a digital image into distinct areas. The major function is to separate the background for processing the significant area during the object evaluation. A proper segmentation is crucial for further progress in image analysis and an improper segmentation will diminish the classifiers performance. It is used in various applications such as agricultural (Payne et al., 2013; Deepa and Geethalakshmi, 2012) and medical (Christ and Parvathi, 2012). The widely used segmentation techniques are thresholding (George et al., 2013) and clustering (Mahjoub, 2011; Brouwer et al., 2010). The recognition of thresholding technique is due to its easiness and uniformity. Depending on image gray levels, thresholding bifurcate the digital image into various regions. The original image is transmuted into grayscale format which can produce more persistent segmented images. "The thresholding classify each pixel in the image into two classes i.e. interest area and background area. The pixels with particular gray level belonged to the class of interest area while pixels with the equivalent gray level belonged to the class of background". The thresholding-based, Otsu method (Otsu, 1979 9) provides gray level histogram (to get optimal threshold) from the grayscale image. Due to wide applications, Otsu method has certain advantages such as optimizing threshold value and processing of gray level image without previous knowledge of the image. Although, this method has disadvantages such as more computational time required for optimal threshold value as number of clusters increases. The clustering technique are used instead of thresholding based method to mitigate the computational time. A clustering technique form the cluster based on similar characteristics of pixel and classified into Hierarchical and Partition-based method. The former method is based on the tree structures in which the roots and the branches indicates the whole database and clusters respectively. The latter method uses optimization technique to optimize the cost function. The basic two types of clustering are hard and soft clustering. Hard clustering is a straightforward technique which segments the image based on pixels belonging to identical clusters. An example of hard clustering is one k-means in which the distance from center is evaluated then each pixel is assigned to closest center. Hard clustering maximize and minimize the intra and inter clustering respectively. Although, k-means is easy and unique, but the algorithm performance is highly influence by initial cluster center. Soft clustering is more realistic as noise exact division does not exist in real life. An example of this technique is Fuzzy C-means in which one pixel can belong to more than one clusters. Under natural environment, FCM is not applicable for image classification but efficient in image segmentation under controlled environment. As, FCM is sensitive to illumination variation that subsume the elements of uncertainty and fuzziness.

Ghabousian and Shamsi (2012) propose an unsupervised algorithm; fuzzy clustering used to segment color images of apples which increases accuracy in segmentation algorithm. This method uses color space L a∗b∗ which provide the best property to segmenting of apple colored images. Alavi (2012) proposes a Mamdani fuzzy interference system (MFIS) based on mozafati date grading. The evaluation based on MFIS model is more accurate (86.00%) than experts and provides better date grading representation. Hambali et al. (2014) proposed a rule based segmentation method that considers IF-THEN rules for image segmentation accurately. TsNKM combines two algorithms: improves thresholding and adaptive K-means. The performance of fruit images are evaluated by four segmentation methods (Otsu, K-means, Fuzzy C-means and TsNKM) based on visualization. The analysis depicts that TsNKM is able to produce highly accurate segmented images. Pham and Lee (2014) proposed a hybrid algorithm based on split and merge approach, used for fruit defect detection. The k-means algorithm is used to split the original image into regions based on Euclidean color distance. Then a merge procedure using minimum spanning tree to merge into similar regions. Mehra et al. (2016) propose tomato maturity based on color and fungal disease. It evaluates the fungus attributes and stem depth of tomato and identifying fungus by using segmentation. In this, thresholding and k-means clustering algorithm are used for segmentation of image and identifying fungus. Jhawar (2016) proposes automatic grading of orange using pattern recognition technique in which two novel techniques: edited multi seed nearest neighbor technique and linear regression based technique results in 89.90% and 97.98% accuracy, although nearest neighbor technique is also extended with 92.93% accuracy. Fig. 5 depicts the accuracy of different segmentation techniques implemented for quality analysis of fruits and vegetables.

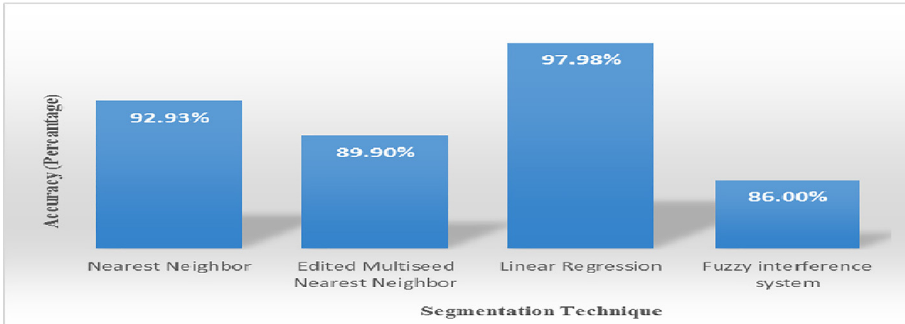

Fig. 5. Efficiency for quality analysis of fruits and vegetables based on segmentation techniques.

2.4. Feature extraction

After image segmentation, features are estimated for further analysis. These features are the basic factors in a computer vision system as they consist of effective data for image perceptive, interpretation, object classification. In this process, extracted features form feature vectors that are classify to recognize the input. These feature vectors defines the object shape uniquely and precisely. The feature extraction aim is to enlarge the rate of recognition by extracting the features. In the food industry, these features give the explicit data that can be considered for quality assessment and analysis. Color, textural and morphological features are frequently used to analyze the defect and maturity of the fruits and vegetables.

2.4.1. Color features

The factors which influence the customer to reject or choose the fruits and vegetables are color. It is the indirect measurement of quality characteristics like freshness, desirability and variety, maturity and safety (Pathare et al., 2013) which is governed by physical and chemical changes, internal biochemical, microbial occurs in ripeness, growth and postharvest processing and handling stages. The color feature is the first and most widely used visual features in image retrieval and indexing. The color feature has many advantages like high efficiency, ease in extraction of color information from images, size and orientation independent, powerful in representing visual content of images, robust to background complications and powerful in separating images from each other. The RGB color space, HSI space, CIELab space is commonly used for color inspection of quality of fruits and vegetables. Once the color spaces have been specified, color feature can be extracted from images. Various color features have been introduced by many researchers that includes, color correlogram, color coherence vector, color moments, and color histogram, etc. Among them, color moment is simple and effective. The most common moments are mean, standard deviation and skewness.

Images are acquired by commonly used RGB color models which is based on primitive colors red (R), green (G), blue (B). This color model separates an image into red, green and blue planes and all the color moments are determined (Mustafa et al., 2011). In an image, for same pixel different RGB devices produces different RGB values, to standardize these values several transformations techniques are used. As RGB is nonlinear with the visual inspection of human eyes, it is therefore not able to analyze the sensory properties of food products. To overcome this, HSI is proposed and developed which is the leading tool for evolving image processing algorithm established on color that are common and received by humans. However, HSI and RGB are similar and are insensitive to meagre variation in color. Therefore, these are not advisory for evaluating transformation of product color during processing. CIELAB color space, characterize all the colors clear to the human eye and was designed to present as device dependent model to be used as reference where 'L' is the measure of lightness, 'a' and 'b' changes the red/green and green/blue balance respectively. It is perceptual uniform such that color differences a human perceives is same as Euclidean distances in CIELAB space. Since the color measured by computer vision can be easily analyze with color obtained from CIELAB color space, it offers a feasible way to evaluate the performance in measuring the object color.

Kondo et al. (2005) uses 4 monochrome CCD cameras and 6 color CCD cameras to acquire digital image of eggplant. The CCD camera with 180 degree rotary tray captures and inspect the entire surface of eggplant. The defect detection and extraction of fruit feature from low color contrast background are not easy. Therefore, a new NIR based color CCD camera was used to extract fruit feature from dark background and detect low contrast defects. Kurita et al. (2006) propose feature extraction of tomato color and shape which is evaluated using top images of different tomatoes, because these are non-trivial information regarding product grading to elevate its market value. Mendoza et al. (2006) uses sRGB, HSV, CIELab color space and image captured were calculated which affects the results. These three color spaces are compared and found that sRGB was powerful to define the mapping between RGB from CCD color cameras and CIEXYZ. CIELAB system is proposed to be the best color space for quantification in foods with curved surfaces.

Xiaobo et al. (2008) propose organization feature parameter based on genetic algorithm. By applying expression tree algorithm high grade judgment ratio were achieved. Blasco and Aleixos (2009a) describes the evolution of computer vision system to analyze the extraction process raw material and classify it that is capable of detecting, sorting and removing unwanted material. Two image segmentation methods are tested: one based on threshold on R/G ratio and other is based on Bayesian linear discriminate analysis. Both methods offers accuracy of 90.00%. Prabha and Kumar (2013) proposes an approach in which mean color intensity from histogram, area, perimeter were extricated from calibration images. Area algorithm and mean color intensity algorithm were refined and their accuracy on maturity detection was assessed with 99.10% and 85.00% accuracy respectively. Kalsom et al. (2014) proposes to measure fruit quality by using visible optical fiber sensor that contain of RGB LEDs with wavelength 635 nm, 525 nm, and 470 nm. The coefficient of determination (R^2 = .879) was obtained by data set at various ripeness indices. This method uses optical instrument which produce excellent and authentic measurement when classifying the index. Dorj et al. (2017) propose an algorithm that utilize the color features to present an estimate of citrus. To obtain good result automated watershed segmentation is done using distance transform and marker controlled watershed algorithm. The proposed algorithm showed correlation coefficient of .93. Pereira et al. (2018) proposed an approach to predict the ripening of the papaya fruit using digital

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Table 2
Comparison of different color features for quality analysis of fruits and vegetables.

Author (s)	Types Of Fruits & Vegetables	Parameters	Color Space	Accuracy
Blasco et al. (2009b)	Pomegranate	Grading by color	Grading by color	90.00%
Liming and Yanchao (2010)	Strawberry	Grading by external quality	CIE Lab	88.80%
Alfatni et al. (2008)		Ripeness inspection	RGB	–
Abdullah et al. (2006)	Carambola	Maturity discrimination	HSI	95.30%
Yi-bin et al. (2006)	Citrus	Maturity evaluation	HSI	–
Vidal et al. (2013)		Color evaluation	RGB	R^2 = .925
Dorj et al. (2017)	Citrus	Grading by color	RGB	0.93
Chong et al. (2008)		Color evaluation	HSI	R^2 = .93
Wang et al. (2012)	Banana	Quality evaluation	RGB	–
Kang et al. (2008)		Color evaluation	CIELab	–
Prabha and Kumar (2013)		Maturity evaluation	RGB	99.10%
Yimyam et al. (2005)	Mango	Sorting by external quality	HSI	–
Kalsom et al. (2014)		Maturity detection	RGB	–
Zou et al. (2010)	Apple	Grading by color	RGB & HSI	–
Garrido-Novell et al. (2012)		Maturity discrimination	RGB	95.83%
Singh Chauhan and Pratap Singh (2012)		Color classification	HSI	100%
Suresha et al. (2012a)		Color classification	RGB	100%
Stefany et al. (2017)		Maturity detection	CIELab	100%
Esehaghbeygi et al. (2010)	Peach	Color and size	HSI	90.00%
Effendi et al. (2009)	Jatropha	Ripeness evaluation	RGB	–
Kondo (2010)	Pear	External quality based	HSI	–
Lino et al. (2008)	Tamato	Color classification	RGB	–
Louro (2006)		Classifying by color and size	RGB	–
Kurita (2006)		Color classification	RGB	
Barnes et al. (2010)		Blemish detection	RGB	
Pereira et al. (2018)	Papaya	Grading by color	RGB	94.30%

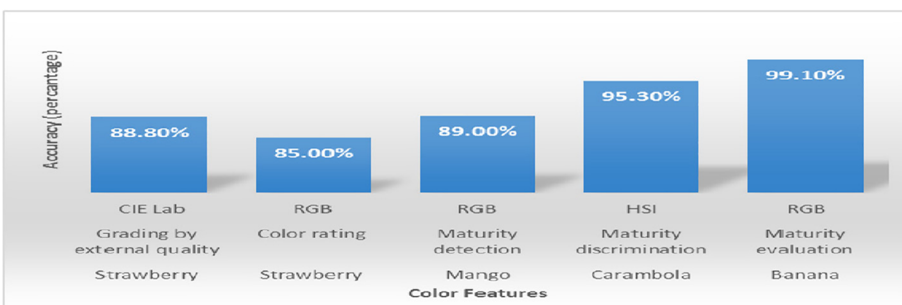

Fig. 6. Efficiency for quality analysis of fruits and vegetables based on color features.

imaging and random forests. The color features are computed from peel that have low computational cost results in 94.30% classification. Table 2 illustrates the quality analysis of fruits and vegetables based on different parameter and color space model employed by numerous researchers. Fig. 6 depicts the accuracy of different color model applied for quality analysis of fruits.

2.4.2. Morphological features

The morphological features (size and shape) are frequently used for classification of fruits and vegetables. In agriculture industry, the size of fruits and vegetables relates to price, therefore in processing stages different size group are allotted for grading of fruits and vegetables. Spherical and quasi-spherical object size of fruits and vegetables inspection is very easy compare to natural irregularity of complex foods. Quantifying the feature size is measured by using projected area, perimeter, length, width, major and minor axis. These features are broadly used in automatic sorting purpose in industries. The area (scalar quantity) calculates the actual number of pixels in the region. Projected area is acquired by pixels of the area. The distance of two neighboring pixels results in feature extraction. Perimeter (scalar quantity) is the distance between the boundaries of region. No matter what shape or orientation, once the object is segmented area and perimeter are stable and efficient. To quantify the size of fruits and vegetables length and width are used. Since the shape of food products is usually change during processing, the orientation at which length and width are calculated needs to be restored in time. The longest line across the object, obtained by the distance of every two boundary pixels is major axis. The longest line drawn across the object perpendicular to the major axis is minor axis. Shape is a critical visual feature for image content description which cannot be defined precisely because it is difficult to measure the similarity between shapes. The two categories of shape descriptor are: region based (based on integral area of object) and contour based (boundary segmented using local features). Shape features are measured by roundness, aspect ratio and compactness. Kondo (2009) uses maximum length, breath and diameter for measuring fruit size. All above features are combined to sort apples (Blasco et al., 2003), dates (Lee et al., 2008a; Lee et al., 2008b), papaya (Riyadi et al., 2007) and eggplant (Kondo et al., 2007). To sort strawberries, lemon and citrus, diameters are used (Khojastehnazhand et al., 2010a; Khojastehnazhand et al., 2010b). Ohali (2011) designed and implemented a prototypical computer vision system based date grading and sorting. The images (RGB) consequently extracts the leading features of date fruit which classifies into three category. The back propagation neural network classifier is used which sort 80.00% dates accurately. To sort potatoes, mangoes, tomatoes, strawberry similar methods are used (Hasankhani and Navid, 2012; Zou et al.,

Table 3
Comparison of different morphological features for quality analysis of fruits and vegetables.

Author (s)	Types Of Fruits & Vegetables	Parameters	Morphological Features	Accuracy
Xiaobo et al. (2008)	Apple	Shape grading	Fourier descriptors	–
Zhang et al. (2012)		Shape grading	Fourier descriptors	95.24%
Ashok and Vinod (2014)		Shape grading	Fourier descriptors	88.33%
Zhang and Wu (2012)	Pear	Physical properties	Depends on size	88.20%
Kondo (2009)		Grading by external quality	Deformability, Complexity, Roundness	–
Blasco et al. (2007)	Citrus	Inspection	Maximum/Minimum diameters	94.00%
Costa et al. (2009)		Quantitative evaluation of shape	Fourier descriptors	–
Rashidi et al. (2008)	Kiwifruit	Shape grading	Length to major diameter ratio	–
Abdullah et al. (2006)	Star	Shape discrimination	–	100%
Ohali (2011)	Date	Grading based on external quality	Fourier descriptor	80.00%
Yimyam and Clark (2012)	Mango	Physical properties	Length and width	–
Khoje and Bodhe (2012)		Physical properties	Fourier descriptors	89.83%
Riyadi et al. (2007)	Papaya	Classification based on shape	Features based on wavelet	98.00%
Sadrnia et al. (2007)	Watermelon	Classification based on shape	Length to width ratio and fruit area to background area	–
ElMasry et al. (2012)		Sorting of irregular potatoes	Roundness, extent, and Fourier descriptors	100%
Dimatira (2016)		Size-Shape	Fuzzy Logic	
Zhang et al. (2014a,b,c,d)	Potato	Irregularity evaluation	Fourier descriptors	98.10%
Chong et al. (2008)	Eggplant	Physical properties	Difference of diameters (max., min.)	–

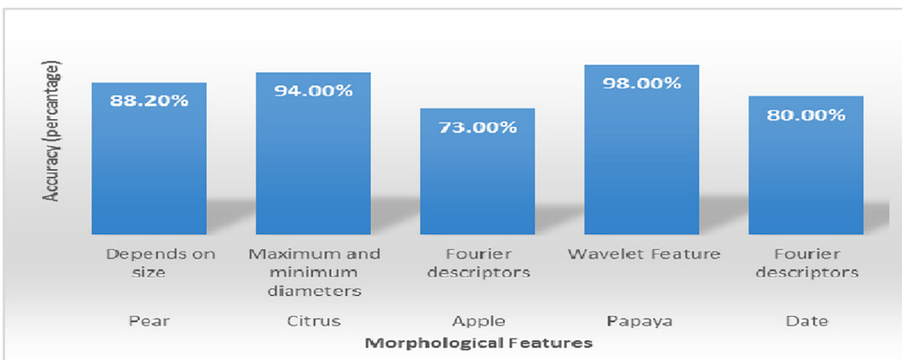

Fig. 7. Efficiency for quality analysis of fruits and vegetables based on morphological features.

2007). Agricultural product has a particular shape or uneven shape having low price or cannot be disposed of (Cubero et al., 2011). Therefore, the essential factor for quality grading and classification in fruits and vegetables is shape. In the quality analysis of food industry, most popular shape features used are convexity, roundness, compactness, length, width, elongation, boundary encoding, length/width ratio, Fourier descriptor and invariant moments. The size and shape features are used for sorting of citrus, apples, peaches, eggplants, potatoes etc. (Zhang et al., 2010; Sadrnia et al., 2007) due to less time consuming and easy realization. The combination of shape features is more sophisticated and reliable (Costa et al., 2009). Dimatira, et al. (2016) uses the fuzzy logic system used to recognize the maturity of tomato fruit. This paper extract color, size and shape features which determines the maturity condition. Table 3 illustrates the quality analysis of fruits and vegetables based on different morphological features employed by different researchers. Fig. 7 depicts the accuracy of different morphological features applied for quality analysis of fruits and vegetables.

2.4.3. Texture features

Texture is very appropriate classification for ample range of image that uses human visual systems for recognition and interpretation. Texture measured from group of pixels represents the distribution of elements and surface appearance and is useful in machine vision that predicts surface in form of roughness, contrast, entropy, orientation, etc. Texture is compatible to maturity and sugar content (internal quality of fruits and vegetables). It is also used to segregate different patterns in images by extracting intensity values between pixels. Texture can be analyzed by quantitative and qualitative analysis. According to quantitative analysis six textural features i.e. contrast, coarseness, line-likeness, directionality, roughness and regularity. According to qualitative analysis four features (Bagril and Johari, 2015) i.e. contrast, correlation, entropy and energy. Different type of texture features are statistical texture, model based texture, structural texture and transform based texture. Statistical texture, extract matrix (gray level co-occurrence matrix, gray level pixel run length matrix and neighboring gray level dependence matrix) which is based on intensity values of pixels. Model based texture includes fractal model, random field model and autoregressive model. Structure texture includes lines, edges that are constructed by pixels intensity. Transform based texture can be extracted spatial domain images. Because of low computational cost and high accuracy, statistical texture is commonly used.

Zhu and Jiang (2007) propose Gabor feature based kernel principal component analysis (PCA) method by combining Gabor wavelet representation of apple images and the kernel PCA method for apple quality inspection using near infrared imaging. The need for local feature segmentation is eliminated by using proposed Gabor kernel PCA which results in 90.60% recognition rate. Quevedo et al. (2008) describes a method in which banana surface was recorded using computer vision system. The over ripening process of banana was represented by an increment in the fractal value derived from texture fractal Fourier analysis. The results shows that spectral Fourier analysis can be used as senescent spotting of banana peel. Kim et al. (2009) uses color co-occurrence method for transformed Hue, saturation and intensity (HSI) images. A stepwise discriminant analysis was used for selecting texture features. The generalized squared distance based discriminant function is used to reduce texture feature. To differentiate citrus peel disease, it is best to reduce HSI which results in accuracy of 96.70%. Zhao et al. (2009) propose a method for detecting citrus peel disease using color texture feature analysis. Stepwise discriminate analysis is used to reduce texture feature. For selected HSI model classification accuracy results in 95.00%. Liming and Yanchao (2010) proposed an automated grading system for strawberry. The dominant color model extract color feature and length of major axis calculate the size and it gave 88.80% and 90.00% accuracy respectively. Khojastehnazhand et al. (2010a) develops an algorithm for classification and sorting based on size and color, volume is calculated for sorting results in 94.04% accuracy. Savakar (2012) developed an algorithm to extract color and texture feature. The three different types of features used are color, texture, combination of both color and texture which are then classify by back propagation neural network. The combination of texture and color feature results in best accuracy among all. Razak et al. (2012) proposed a method and algorithm that uses digital fuzzy image processing, content predicted and statistical analysis to determine the grade of mango production. This system design and develop an adequate algorithm for detecting and sorting the mango at more than 80.00% accuracy in grading compared to human expert sorting. Nozari and Mazlomzadeh (2013) use adaptive network fuzzy interference system as a decision making technique to classify the Mozafati dates based on weight and some geometric parameters. Four date parameter include the weight, length, width and thickness are graded using fuzzy system resulting in 93.50%. Pan et al. (2016) proposed local relative phase binary pattern (LRPBP) based on LBP and texture features results in 95.83% accuracy. Jana et al. (2017) propose an approach for different types of fruits. The segmented image results in color features and gray level co-occurence matrix results in texture features which are classified by support vector machine. It works well for embedded systems and single board computers. Li et al. (2017) proposed a method which combines color, shape and texture features to solve the problem of segmenting the target and background of apple picking robot in complex background. The statistical method use gray scale to extract texture feature, which results in superior to other algorithm. Moallem et al. (2017) propose an algorithm for apple grading in which defect segmentation is achieved using Multi-Layer Perceptron (MLP) neural network. Then statistical, textural, geometric features are extracted and comparison between classifications is done by using Support Vector Machine (SVM), MLP, K-Nearest Neighbor (KNN). The SVM classifier results in 89.20% and 92.50% accuracy for defected and healthy apples. Sahu and Potdar (2017) propose an algorithm to identify defect and maturity of mango fruit based on quality ratio. If the value of quality ratio is greater than threshold value, the fruit is rotten. If the value of quality ratio is less than threshold value, the fruit is good. Therefore, proposed algorithm sort mango fruit based on quality which is essential for value addition of fruits. Naik and Patel (2017b) propose a mango grading based on maturity and size feature. To predict the maturity mean intensity algorithm in CIELAB color space and thermal camera is used. The size of mangoes are predicted by weight, eccentricity and area which results in 89.00% accuracy with 2.3 s. Rong et al. (2017) proposes a sliding comparison window local segmentation algorithm that segments various types of surface defects like insect injury; wind scarring; thrips scarring; copper burn etc. which detect correctly 97.00% of defective orange. Table 4 illustrates the quality analysis of fruits and vegetables based on texture features employed by different researchers.

2.5. Classification

The essential feature for food quality evaluation is classification which contribute a structure in which artificial simulation of human thinking is done to guide humans form sophisticated judgments instantaneously, correctly and persistent. By using image processing techniques, fruits and vegetables images can be described by set of features such as color, size, shape and texture. These features are used to form training set, then classification algorithm is applied to extract knowledge base which make a decision of unknown case. In computer vision system, a wide variety of methods: KNN, SVM, Artificial Neural Network (ANN), Deep Learning/Convolutional Neural Network (CNN) have been developed for classification in food quality evaluation. KNN targeted on similitude of samples measured by distance metric. It firstly select K number of neighbors then based on Euclidian distance in each category, number of data point counted and then a new point is elected where new point can be counted. SVM is a powerful classification algorithm in which both linear and non-linear data is classified. It non-linearly maps data to a high dimensional space by

Table 4
Comparison of different texture features for quality analysis of fruits and vegetables.

Author (s)	Types Of Fruits	Parameters	Accuracy
Zhang et al. (2014c)	Apple	Stem end/Calyx	95.24%
Li et al. (2017)		Shape, Texture	
Jana et al. (2017)		Color, Texture	
Pan et al. (2016)		Texture	95.83%
Moallem et al. (2017)		Statistical, texture and geometric features	92.50%
Deepa and Geethalakshmi (2012)	Mix	Shape, Texture	Texture96.00% Shape 100%
		Shape, Texture	
		Shape, Texture	
Savakar (2012)		Color, Texture	Chickoo 94.00%
		Color, Texture	Apple, Lemon 93.00%
		Color, Texture	Mango, Orange 92.00%
Khoje et al. (2013a,b)		Texture	Guava, Lemon 96.00%
Nozari et al. (2013a,b)	Date	Length, Width, Thickness	93.50%
Alavi (2012)		Size	86.00%
Pourjafar et al. (2013)		Length, Width, Thickness	90.00%
Liming and Yanchao (2010)	Strawberry	Color, Size	Color: 88.80%,
		Color, Size	Size: 90.00%
Khojastehnazhand et al. (2010b)	Lemon	Color, Size	94.04%
Razak et al. (2012)	Mango	Size, color and skin	80.00%.
Sahu and Potdar (2017)		Global features	–
Naik and Patel (2017)		Color and texture	91.00%
Rong et al. (2017)	Orange	Morphological feature	97.00%

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using kernel functions. For 2-class problems, SVM finds the linear optimal hyper plane such that the distance between support vectors (extreme points of both the classes) can be maximized. ANN are basically the computer programs which are biologically influenced to simulate the way in which the human brain process instruction.

Development in deep learning and convolutional neural network are very efficient for fruit classification and recognition. Deep learning learns the image features and extracts contextual details and global features that will help in reducing the error remarkably. Recently, the deep learning received major demand than any other machine learning algorithms. However, the associated research in fruit classification using this method is less presently. When Hinton's team got the champion of the ImageNet image classification (Krizhevsky et al., 2012), deep learning received main attention. To identify local and global features, edge and texture features are used. Using deep neural networks, a fruit detection system is proposed (InKyuSa et al., 2016) and this model is trained again to perform the detection of seven fruits. To train CNN, input image and associated label are needed. CNN automatically extracts several features.

Unay and Gosselin (2005) develops artificial neural network based segmentation, features are extracted from them and nearest neighbor, linear discriminant, Adaboost, support vector machine and fuzzy nearest neighbor classifiers were used to grade them. Adaboost and SVM shows highest accuracy. Vijayrekha (2008) uses the images that are highly correlated in the narrow bands. The defects are segmented using multivariate image (MIA) analysis based on multi way PCA method. MIA groups all the pixels with same spectral properties into a single cluster. Therefore, the external defects can be easily identified. Wang et al. (2009a,b) develop algorithm for apple in which median filter is used then segmentation is done by region growing followed by support vector machine for classification. Radojevic et al. (2011) combines analysis of apple fruit 256 gray level images and parameterization algorithm. It is based on digital pattern recognition method, linear fitting and numerical integration which is used in reliable fruit sorting. Unay et al. (2011) propose specific segmentation by minimal confusion with stem/calyx areas on multispectral images, textural, geometric and statistical features are extracted from segmented area. In this multi category grading achieve 93.50% overall accuracy. Gopal et al. (2012) propose classification based on median of PDF. The same are classified using histogram intersection to avoid mismatch in grading. Dubey and Jalal (2012) propose texture and color feature extraction of apple with classification as complete local binary pattern. Borse and Jhuria (2013) propose a method in which apple scab and apple root disease are detected. The classification is done by texture, color and morphology feature which give 90.00% accuracy as best for morphology feature extraction.

Zhang et al. (2014d) proposed a fitness scaled chaotic artificial bee colony (FSCBC) algorithm and feed forward neural network (FNN) as a hybrid classification method. In this, fruits images with squared window, whose color, texture and shape features are extracted and the dimension is reduced by principal component analysis. These extracted features are classified by FSCBC-FNN algorithm with 89.10% accuracy. Wang et al. (2015) developed a system consist of wavelet entropy (WE), principal component analysis (PCA), feedforward neural network (FNN) trained by fitness scaled chaotic artificial bee colony (FSCABC) and biogeography based optimization (BBO). The classification performance showed the proposed "WE+PCA+FSCBC-FNN" and "WE+PCA+BBO-FNN" achieve same accuracy of 89.50%. Dubey and Jalal (2015b) propose combination of color coherence vector, Zernike moments and complete local binary pattern which gives 95.94% accuracy. Nandi et al. (2016) proposed a machine vision based technique for grading of mangoes. In this techniques several feature are extracted followed by support vector regression then fuzzy incremental learning algorithm has been used which grade nearly 87.00% accurately. Zhang et al. (2016) proposed a classification based on biogeography based optimization and feedforward neural network. The results showed by fine fold stratified cross-validation with 89.11% overall accuracy. Jawale and Deshmukh (2017) proposed automatic inspection by using modernized image processing and thermal camera which use bruise detection system for detection of fruit diseases. By using artificial neural network working in real time results in sufficient speed and accuracy. Zaborowicz et al. (2017) uses artificial neural modelling for assessing the quality of greenhouse tomatoes. By taking two digital images, stem and front of tomato performs correct classification. Cavallo et al. (2018) proposed an approach to enable analysis on packaged fresh-cut lettuce. A deep learning architecture, based on convolutional neural network (CNN) was used to identify vegetable with minimum color distortions. For classifying the quality level, CNN select the region. The classification is done by 3-nearest neighbor in the CIELAB color space. Sendin et al. (2018) proposed object-wise partial least square discriminant analysis models for multi spectral imaging to grade whole white maize and undesirable with cross-validated coefficients of determination and classification accuracies ranging from 83% to 100%. Table 5 illustrates the quality analysis of fruits and vegetables based on different classification techniques employed by different researchers. Fig. 8 depicts the accuracy of different classification techniques applied for quality analysis of fruits and vegetables.

3. Defect detection of fruits and vegetables

In commercial sorting machines, visual analysis of fruits and vegetables with respect to color, texture, size and shape by traditional computer vision is earlier computerized. Defect detection is still a defy task due to huge variation of defect types (Unay and Gosselin, 2006). As disease appear on fruit, it is essential to detect the fruit disease automatically. Fruit disease causes losses in yield and quality appeared in harvesting. The common disease of apple fruits are scab, rot and blotch. With increased high quality expectations in food products, the need for authentic and objective quality determination in food products progress continuously. To manage these requirements, computer vision system provides automated, cost-effective and non-destructive technique. This image processing based inspection technique has various applications in fruits and vegetables quality evaluation.

Xing et al. (2005) use principle component analysis for hyperspectral images. The second and third principal components images are convenient for identifying the presence of bruises. The classification results 93.00% of non-bruised apples. Blasco et al. (2007) propose an algorithm for citrus fruit using region oriented segmentation to detect. The region of interest consist of stem, sound peel and defects. Assume that the maximum surface of fruit is of sound peel, the proposed algorithm detect the defect with 95.00% accuracy. Zou et al. (2010) use different color cameras to detect peel from surface of fruits and vegetables. It detects the region of interest in a given apple image. The classification error of blemished apples reduced from 21.80% to 4.20% for three camera system. Li et al. (2013a) develops spatial feature extraction from hyperspectral images. The combination of both image processing chemo metric tools is useful to detect defect. Hu et al. (2013) propose an algorithm for banana to segment using K-means clustering at various ripening stages. The first K-means clustering image segmentation segments the contours of banana finger. The second K-means clustering quantify the damage lesions and spots on banana surface.

Arakeria and Lakshmana (2016) proposes an effective tomato fruit grading system based on computer vision techniques, consists

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Table 5
Comparison of different classification techniques for quality analysis of fruits and vegetables.

Author (s)	Input Image	Pre-Processing	Feature Extraction	Classifier	Accuracy
Unay and Gosselin (2006)	Jonagold Apples	Artificial Neural Network based segmentation	Average, Standard deviation, Defected ratio	NN, LDA, Adaboost, SVM, FNN	90.30% accuracy for Adaboost and SVM
Pydipati et al. (2006)	Citrus	Edge detection	Color co-occurrence methods	Generalized Squared Distance	>95.00%
Zhu and Jiang (2007)	Golden delicious apples	Gabor wavelet decomposition	Gabor feature vectors	PCA	90.50% accuracy for Gabor-kernel PCA
Vijayarekha (2008)	Normal apples	Reorganization of multivariate image	Score plots, Scatter plots	PCA	–
Wang et al. (2009a,b)	Fuji apples	Vector Median Filter	Region growing	SVM	–
Kim et al. (2009)	Grapes	ROI Cropping	Intensity texture feature	Discriminant Analysis	96.00%
Rocha et al. (2010)	–	K-means with 2 clusters	GCH + CCV + BIC + Unser (Fusion)	Multiclass SVM	97.00%
Arivazhagan et al. (2010)	–	Cropping	Co-occurrence features such as contrast, energy, local homogeneity, cluster shade and cluster prominence	Minimum distance classifier	86.00%
Radojevic et al. (2011)	Apples	Conversion of color to gray scale image	Digital parameterization for measuring shape and size	–	Parameterization is effective
Unay and Gosselin (2006)	Jonagold apples	Segmentation based on MLP method	Statistical, Geometric, Texture features	LDC, K-NN, Fuzzy K-NN, SVM	Statistical give better performance
Faria et al. (2012)	–	K-means with 2 clusters	Color, Texture and Shape	Classifier Fusion	98.80% ± 0.9
Danti et al. (2012)	–	Cropping and resizing	Mean and range of Hue and Saturation	BPNN Classifier	96.40%
Suresha et al. (2012b)	–	Watershed segmentation	Texture features	Decision-tree classifier	95.00%
Ghabousian and Shamsi (2012)	Normal apples	Active contour model	Fuzzy C- Means algorithm	–	–
Gopal et al. (2012)	Red delicious, Fuji, Royal Gala	Conversion from RGB to HSI model	Mean, Median, PDF, Histogram	–	–
Arlimatti (2012)	Normal apples	Conversion in HSV color space and thresholding, Transform in several planes	Mean, Standard deviation	Nearest neighbor classifier	–
Dubey and Jalal (2015b)	Normal apples	Conversion in CIELab, K means clustering	GCH, LBP, CLBP, GCH, CCV	Multiclass SVM	95.94% for CLBP
Dubey and Jalal (2014)	–	K-means with 2 clusters	ISADH	Multiclass SVM	99.00%
Chowdhury et al. (2013)	–	–	Color Histogram + Texture	Neural networks	96.55%
Pujari et al. (2013a)	–	K-means	Texture features	BPNN Classifier	84.65% for normal type and 76.60% for anthracnose affected type
Pujari et al. (2013b)	–	–	Color features + GLCM	BPNN Classifier	89.15% for normal type 88.58% for affected type
Borse and Jhuria (2013)	Normal apples	Conversion from RGB to HSI color model	Color: Histogram difference	Back propagation Neural Network	Color and Morphology gives best results.
Pujari et al. (2014)	–	Shade correction, Removing artifacts and Formatting	Color + Texture features	ANN/Knowledge base Classifier	87.80%
Kanakaraddi et al. (2014)	–	Median filtering	Color features	Decision tree	–
Ashok and Vinod (2014)	Normal apples	CIELab space, global threshold segmentation	Mean Boundary Gradient	Probabilistic Neural Network	88.33%
Suchitra et al. (2013a,b)	Guava + Lemon	–	Curvelet based texture feature	SVM + PNN	96.00% for SVM
Rokunuzzaman and Jayasuriya (2013)	Tamato	–	Color feature	Rule based + NN	84.00% for rule based 87.50% NN
Zhang et al. (2014d)	Any	Split & Merge	Color, Texture, Shape	FSCBC + FNN	89.10%
Wang et al. (2015)	Any		K-Fold Stratified	WE + PCA+BBO-FNN	89.50%
Zhang et al. (2016)	Any	4-step	Color, Texture, Shape	BBO + FNN	89.11%
Cavallo et al. (2018)			No need	Deep learning/CNN	
Sendin et al. (2018)	Maize			PLS-DA	83–100%
Jawale and Deshmukh (2017)	Apples			ANN	
Zaborowicz et al. (2017)	Tomato			ANN	
Nandi et al. (2016)	Mangoes		Shape	Support Vector Regression	87.00%

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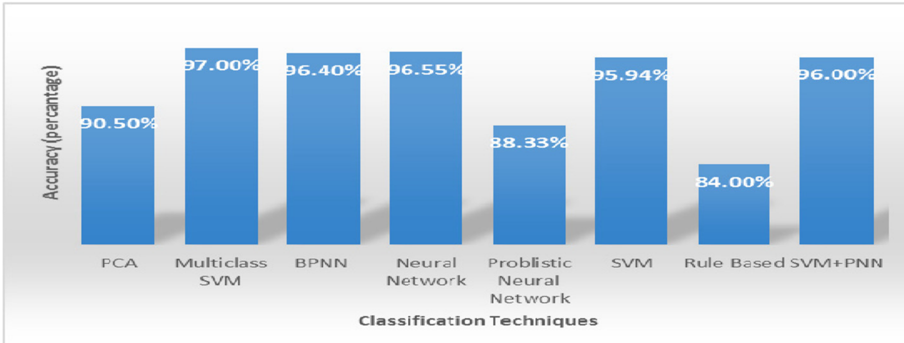

Fig. 8. Efficiency for quality analysis of fruits and vegetables based on classification techniques.

of two phases: development of hardware and software. The developed hardware captures the image and move the fruit to the appropriate canister without manual intervention. The software develop by image processing techniques to inspect the fruit for ripeness and defects which yields 96.47% efficiency in evaluating the quality of the tomato. Si et al. (2017) propose a process in which L/W ratio and tuber is measured and is compared with manual caliper measurements exhibit 96.00% accuracy. Ali and Thai (2017) develop a system consist of mechanical, electrical parts. The grading of fruit is depends on external quality factor such as decay and surface defect. This automated system has saved effort, time and has better efficiency. Cheng et al. (2017) uses multiplicative scatter correction preprocessing followed with regression coefficient of partial least squares to extract feature wavelengths. This paper shows hyperspectral imaging can be a reliable mechanism for detection of apple internal qualities. Table 6 illustrates

Table 6
Comparison of different defects for quality analysis of fruits and vegetables.

Author (s)	Types Of Fruit & Vegetables	Parameters	Type of CVS	Methods	Accuracy
Zou et al. (2010)	Apple	Defect detection	TCVS	Color Camera	89.00%
Unay et al. (2011)		Quality Grading	MCVS	Statistical, Syntactical classifiers	93.50%
Unay and Gosselin (2006)		Defect Segmentation	MCVS	ANN	–
Baranowski et al. (2012)		Bruise Detection	HCVS	PCA, MNF, SIMCA, LDA, SVM	–
Kim et al. (2008)		Defect and feces detection	MCVS	–	–
ElMasry et al. (2008)		Bruise detection	HCVS	PLS, SDA	93.95%
Gomez et al. (2008a,b)		Rottenness detection	HCVS	LDA	91.20%
Nicolai et al. (2006)		Bitter pit detection	HCVS	PLS	–
Ariana et al. (2006a)		Defect detection	MCVS	ANN	95.40%
Kim et al. (2007)		Defect detection	HCVS	BR	99.50%
Xing et al. (2007)		Bruise detection	HCVS	PCA, PLSDA	86.00%
Xing et al. (2005)		Bruise detection	MCVS	PCA, MT	86.00%
Bennedsen et al. (2005)		Defect detection	MCVS	Rotating	90.00%
Bennedsen et al. (2007)		Defect detection	MCVS	PCA, ANN	79.00%
ElMasry et al. (2009)		Injury detection	MCVS	ANN	98.40%
Zhang et al. (2014c)		Bruise detection	HCVS	MNF	97.10%
Ashok and Vinod (2014)		Defect detection	TCVS	FDA	88.33%
Moallem et al. (2017)		Defect detection	TCVS	SVM, KNN, MLPs	92.50%
Qin et al. (2012)	Citrus	Canker detection	MCVS	BR, T	95.30%
Blasco et al. (2009a)		Skin damage detection	MCVS	Bayesian discriminant analysis	86.00%
Blasco et al. (2007)		Peel defect detection	TCVS	Region oriented segmentation	95.00%
Li et al. (2013b)		Common defect detection	TCVS	Lighting transform and image ratio	98.90%
Li et al. (2011)	Orange	Common defect detection	HCVS	PCA	93.70%
Gomez-Sanchis et al. (2008b)		Light correction	HCVS	Light correction	–
Haff et al. (2013)		Fly infestation detection	HCVS	Particle analysis	–
Gomez-Sanchis et al. (2012)		Rottenness detection	HCVS	ANN, DT	98.00%
Zhao et al. (2010)	Pear	Bruise detection	HCVS	PCA, MLC, EDC, MDC, SAM	93.8–95%
Hu et al. (2013)	Banana	Segmentation	TCVS	Two-step k-means	–
Nagata et al. (2006)	Strawberry	Bruise detection	HCVS	LDA, ND, ANN	100%
Qin and Lu (2005)	Cherry	Pit detection	HCVS	NN	97%
Wang et al. (2011)	Jujube	Defect detection	HCVS	JMP, MA	97%
Razmjooy et al. (2012)	Potato	Quality inspection	TCVS	SVM, KNN, MLP	–
Si et al. (2017)		Tuber detection	TCVS	R/W ratio	96.30%
Ariana et al. (2006b)	Cucumber	Bruise detection	HCVS	PCA, BR	75–95%
Liu et al. (2006)		Chilling injury detection	HCVS	BR, PCA	>90%
Lu and Ariana (2013)		Fly infestation detection	HCVS	PLS	88–93%
Gowen et al. (2008)	Mushroom	Bruise detection	HCVS	PCA	79–100%
Gowen et al. (2009)		Freeze damage detection	HCVS	PCA, LDA	95%
Taghizadeh et al. (2011)		Enzymatic browning	HCVS	PLS DA	–
Ali and Thai (2017)	Apple + Mango	Surface Defect	TCVS	–	–
Wang et al. (2009a)	Onion	Skin disease detection	HCVS	MS	–
Arakeria (2016)	Tomato	Defect detection	TCVS	ANN	96.47%
Mehra et al. (2016)		Maturity and Defect detection	TCVS	K means	–

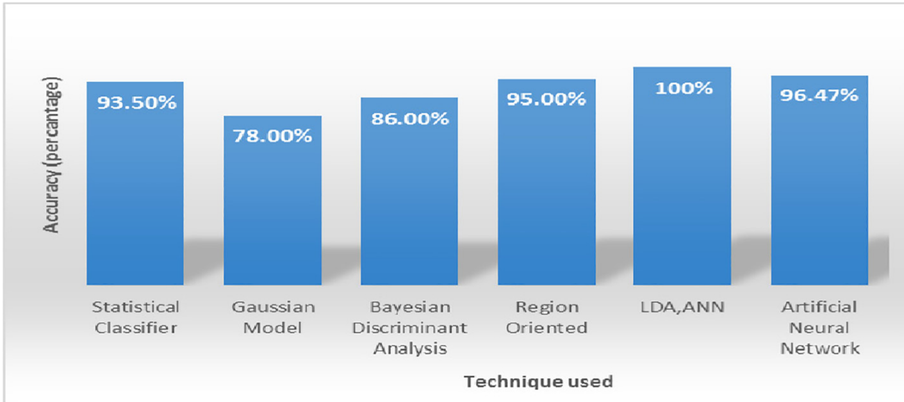

Fig. 9. Efficiency of different defect detection techniques for quality evaluation of fruits and vegetables.

the quality analysis of fruits and vegetables based on different defect detection technique employed by different researchers. Fig. 9 depicts the accuracy of different defect detection applied for quality analysis of fruits and vegetables.

4. Challenges

Image processing and computer vision system are scientific mechanism in agriculture and industrial mechanism due to remarkable performance, growing enhancement in cost, easy to use and algorithmic robustness. Traditional, multispectral and hyperspectral computer vision system are presently extensively used for quality evaluation of fruits and vegetables. The color, size, shape, texture and defect are common features that are inspected by traditional computer vision system (TCVS). To enhance the TCVS, multispectral and hyperspectral computer vision system provide dynamic tools to few defects which are challenging to detect with TCVS due to dominance of spectral images. The various challenges to beaten the defect detection more accurately which includes uneven distribution of light on arch surface, powerful wavelength selection for different application, stem/calyx recognition, surface assessment, lengthy time exhausting of acquisition and processing for spectral image and different defects discrimination, etc. Instead of using particular features like color, size, shape, texture in grading, other features should also be tested in order to improve the outcomes. Also, using same weight value for all features, tuning the weight value may improve the performance. The major advances in Terahertz imaging, Raman imaging, 3D technique can be used in quality analysis of fruits and vegetables.

5. Conclusion

This paper highlights the use of image processing and computer vision technology in the field of food industry and agriculture. The most important quality characteristics of agricultural products are size, color, shape, texture and defect. To replace manual inspection of food, computer vision system is used which provide authentic, equitable and non-destructive rating. The computer vision based quality inspection comprises of four main steps, namely, acquisition, segmentation, feature extraction and classification. In this paper, an attempt has been made to explore and compare the various methods/algorithms proposed by researchers in each step. It can be concluded from the extensive survey carried out in this paper that although number of researchers have proposed various methods for the quality inspection of fruits and vegetables still a robust computer vision based system with improved performance is required to be built.

In the literature the images of fruits and vegetables are captured mainly from one direction. However, the system performance may improve by considering the images of fruits and vegetables captured from different directions. Authors have utilized different color spaces for the color based feature extraction, still one may explore combination/ other color space to improve the performance. It can also be concluded from the work carried out in this paper that one can include the images from different regions to make the system regional bias free. In the work reported in literature, fruit and vegetable grading, sorting and disease recognition are done on single fruit. A generalized system may also be designed to grade or sort and detect the defects of multiple fruits and vegetables.

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Conflict of interest

Authors do not have any conflicts.

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