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REVIEW ARTICLE

Computer vision based automated mango grading – a review

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ABSTRACT

Mango (*Mangifera indica* L.) is one of the most famous fruits and is in great demand worldwide. During exports and local mango marketing, quality assessment of mangoes is crucial. It is achieved by a post-harvest process of mango grading. Quality evaluation based on appearance features like ripeness, size, shape and defect, directly affect customer satisfaction and thereby vendor's economic gains. Such appearance based grading is usually done by humans just by inspection with naked eye. However manual sorting could be inconsistent, inaccurate, time-consuming and labor intensive. Computer vision based mango grading, will lead to consistent, accurate and reliable sorting. In recent years many researchers have made an attempt to perform mango classification/grading using image processing and machine learning techniques. A detailed study of such works, performing mango classification based on grading parameters is done and a precise summary is presented here.

Keywords: Postharvest operation, mango grading, computer vision, machine learning, image processing

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INTRODUCTION

India is a leading producer and exporter of many fruits and vegetables like mango, banana, papaya etc. (APEDA fruits and vegetables). Mango is the most popular fruit also known as 'King of Fruits'. Mangoes in India have a great domestic demand and Uttar Pradesh, Andhra Pradesh, Karnataka, Bihar, Gujarat and Tamil Nadu are main mango producing states (Horticultural statistics, 2018). India is also a prominent mango exporter. In 2018-19 it has exported 46510.27 MT of fresh mangoes to the world, worth Rs. 406.45 crores/ 60.26 Millions USD (APEDA export statistics). Quality inspection of delivered mangoes in domestic and global market can be accomplished by a post-harvest operation of mango grading. Mango grading is the process of classifying/sorting mangoes according to different parameters like size, ripeness, shape, defects, firmness, nutrients etc (Naik, 2019; Ibrahim et al., 2016; Naik et al., 2015). Proper grading helps to examine if delivered mango meets customer's expectations. It can assist in taking appropriate marketing, transport, packaging and price related decisions. Such grading if performed according to pre-defined government standards can open up new export opportunities for vendors (Nandi et al., 2016; Mahajan et al., 2019; Agmark standards). Mango quality inspection is usually carried out manually just by observation. However, this can be significantly inaccurate, inconsistent, time consuming and labor intensive. A better automated solution is essential. In recent years, applications of computer vision techniques for agricultural operations has significantly increased. Soil monitoring, crop disease prediction, yield estimation, leaf classification etc. are few examples

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(Ahmed et al., 2016; Roya et al., 2019; Chouhan et al., 2020).

Computer vision based techniques can also be applied for mango grading, leading to better accurate, consistent, reliable and efficient sorting. Ripeness, size, defect and shape are some important appearance based parameters. A lot of research is going on in appearance based mango grading using image processing and machine learning techniques. An extensive study of such research works is carried out and a comprehensive parameter-wise survey is presented in this paper. Main objective of this study is to provide detailed overview of ripeness, size, defect and shape based mango classification. The paper is organized into following sections: General mango grading methodology, ripeness based analysis, size based analysis, defect based analysis, shape based analysis, multiple parameter based mango grading and conclusion. This survey would be helpful to researcher's willing to perform mango quality assessment using image processing techniques. It gives a parameter wise survey, hence can provide relevant inputs regarding features to be extracted and machine learning techniques to be applied for single parameter classification works. As far as our knowledge, this is a first survey including mango classification works covering multiple parameters. Techniques covered in it can also be applied to classification of other fruits.

MANGO GRADING METHODOLOGY

This section gives an overview of computer vision based mango grading system utilized in most of the research works. In general, the steps involved in all the vision based mango classification works are shown in Figure 1. Mango image acquisition, image pre-processing, segmentation/background removal, feature extraction and classification are some of the important steps of mango classification system.

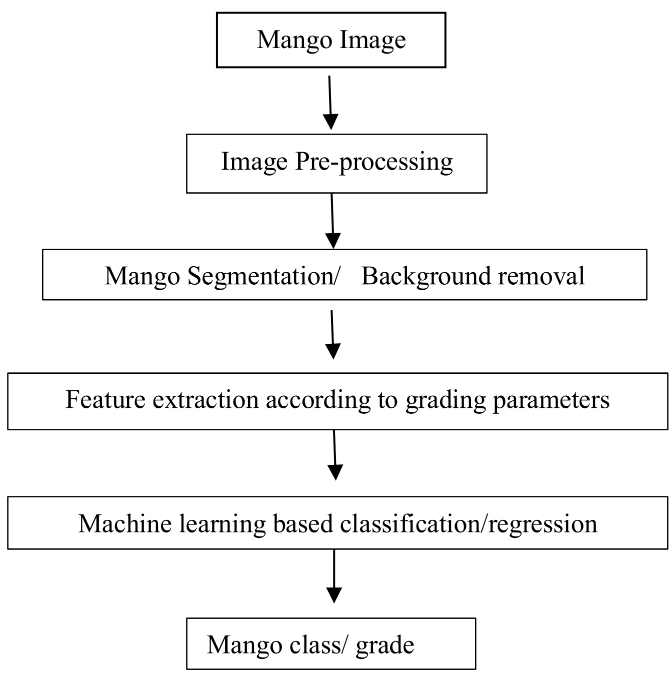

Figure 1: General mango grading methodology

Mango image acquisition

Image acquisition is the first step in vision based grading system. Performance of a vision based grading system largely depends on quality of images acquired, hence proper image acquisition is essential. Colored mango images are usually acquired in digital format using camera, mobile phones etc. In order to control the lightening conditions lamps or bulbs at different angles are utilized. A white background is used to facilitate easy mango segmentation (Ganiron Jr et al., 2014; Naik et al., 2015; Ibrahim et al., 2016). Grading can be performed using single or multiple mango views. A specialized mango rotation setup is essential for multiple view acquisition (Vélez-Rivera et al., 2013). Mango video acquisition can also be done, while mango passes on conveyor belt (Nandi et al., 2016). Video frame extraction has needs to be performed in this case. Usually each image consists of single mango. However, on-tree size estimation was performed by Behera et al. (2018) in which each image consisted of multiple mangoes. A summary about image acquisition and datasets has been presented in Table 1.

Image pre-processing

In order to facilitate better image analysis and feature extraction, numerous image pre-processing operations such as noise removal, image enhancement, histogram equalization, contrast sharpening, morphological operations (erosion, dilation), image smoothening, brightness improvement, shadow elimination etc. are applied (Bermúdez et al., 2013; Sa'ad et al., 2015; Naik et al., 2015; Ibrahim et al., 2016, Sahu and Potdar., 2017). Smaller images often take lesser time for processing hence image resizing is performed (Naik et al., 2015; Ibrahim et al., 2016). Acquired images are usually in RGB color format, however many research works have explored the HSV, HSI, CIELab, YCbCr color models. Hence conversion of RGB to other formats is also an essential pre-processing step. Performing appropriate image pre-processing tasks can help in improving classification results. Image pre-processing operations are generally implemented in MATLAB or python.

Mango segmentation/ background removal

The acquired mango image generally consists of mango with a background. In order to extract mango features, it should be first segmented out from background i.e background should be eliminated. It is achieved by applying appropriate thresholding technique in which pixels above or below certain threshold are considered as mango pixels and remaining as background. Such thresholding can be applied to any of the component of different color spaces. Eg thresholding of Cb component (YCbCr color space) (Bermúdez et al., 2013; Ganiron Jr et al., 2014). Different thresholding techniques like simple thresholding (Sahu and Potdar, 2017; Khalid et al. 2017), Otsu thresholding (Nambi et al., 2016), adaptive thresholding (Sa'ad et al., 2015; Limsripraphan et al., 2019) can be utilized.Sometimes background removal is also considered as pre-processing step.

Feature extraction

After mango is segmented from background, features according to grading parameters are extracted from segmented image. Features are image properties that can help in distinguishing mangoes belonging to different categories. Color features are extracted for ripeness analysis (Vélez-Rivera et al., 2013; Pandey et al., 2014b, Limsripraphan et al., 2019). Geometric properties like area, perimeter, major axis, minor axis are computed for size estimation (Pandey et al., 2014a; Naik et al., 2015). Shape related properties like eccentricity, cross-ratio (Naik et al., 2015), Fourier descriptors (Sa'ad et al., 2015; Nandi et al., 2016; Ibrahim et al., 2016) are obtained for shape analysis. Defect area is computed for defect based analysis (Ganiron Jr et al., 2014; Pandey et al., 2014b; Nandi et al., 2016). Histogram analysis, ellipse fitting, contour detection, contour filling, edge detection, image binarization etc. are some of the image processing methods utilized for feature extraction. Once features have been extracted a feature vector is formed which is given as test input to pre-trained machine learning model.

Classification/ regression

Applying the pre-trained machine learning model to extracted features in order to predict mango category is the next step. A mango grade/category can depend on multiple features, hence a machine learning model is necessary for classification. Machine learning model tries to learn hidden patterns present in given features and derive conclusions based on them. Different machine learning classifiers like support vector machines (Sa'ad et al., 2015; Agilandeeswari et al. 2017; Limsripraphan et al., 2019), decision trees (Mim et al., 2018), naïve bayes (Bermúdez et al., 2013; Limsripraphan et al.,2019), neural networks (Yossy et al. 2017; Alejandro et al., 2018), fuzzy classification (Pandey et al., 2014a; Naik et al., 2015; Nandi et al., 2016), k-nearest neighbor (Ganiron Jr et al., 2014) etc can be employed for mango classification. Parameter specific classification can predict mangoes as (unripe/midripe/overripe), (small/medium/large), (deformed/well-formed) etc.Regression can be usedto predict the mango shelf-life(Nandi et al., 2016), mango length, breadth etc. Performance of mango classification/regression is generally measured in terms of accuracy, error rate, precision and recall.

Table 1: Image Acquisition and Dataset Details

Ref	Image Acquisition Device	# of mango views	Image resolution	Mango variety	Dataset Size
Naik (2019b)	IPhone 4S	1 (top)	2448 * 2448	Kesar	2432 (Naik 2019a)
Agilandeeswari et al. (2017)	Kent dataset- Canon EOS 550D	2		Kent	100 (COFILAB Kent)
Nandi et al. (2016)	CCD Camera(10 MP) - video mode	1	640 * 480	Kumraphali, Amrapali, Sori, Langra, Himsagar	2184
Limsripraphan et al. (2019)	Kent dataset- Canon EOS 550D	2	5184 * 3456	Kent	100 (COFILAB Kent)
Ibrahim et al. (2016)	CMOS camera – 2MP	2 (top, side)	1600 * 1200	Harumanis	180
Naik et al. (2015)	IPhone 4S	3	2448 * 2448	Kesar	900
Mim et al. (2018)	Canon Digital IXUS 400	1	500 * 1000	Himsagor	100
Sahu and Potdar (2017)	Kent dataset- Canon EOS 550D	2	1200 * 800	Kent	100 (COFILAB Kent)
Vélez-Rivera et al. (2013)	Rebel XS W18-55ls Canon	4	3888 * 2592	Manila	117
Bermúdez et al. (2013)	Not mentioned	1	480 * 352	-	150
Nambi et al. (2016)	DSLR- Nikon D60	1	-	Alphonso	114

Sa'ad et al. (2015)	Basler ac1600-20gc Gig camera	1		Harumanis	300
Ganiron Jr et al. (2014)	Canon Digital IXUS 400	1	640 * 480	-	140
Nagle M. et al. (2016)	USB-camera (Logitech C905)	1		Nam Dokmai, MahaChonak	375 each
Patel et al. (2019)	RGB camera (UI-1225LE-CHQ)	6	752 * 480	Chausa, Dashehari	180
Alejandro et al. (2018)	Camera	1		Carabao	120
Pandey et al. (2014a)	Nikon DSLR D90	1	640 * 480	Totapuri, Badami, Neelam	100
Momin et al. (2017)	Sony CCD ICX205AK	1	980 * 880	Three varieties	120
Rojas-Cid et al. (2018)	Genius ilook 300 webcam	1	640x480	Mexican mangoes	62
Yossy et al. (2017)	Webcam	1		Gincu	52

RIPENESS BASED ANALYSIS

Mango ripeness is an important grading parameter that directly facilitates transportation and packaging related decisions, thereby reducing food wastage (Nandi et al., 2016; Mim et al., 2018). Mango maturity can be correlated with its physiochemical and color properties. As mango ripens, its firmness decreases, total soluble solids(TSS) increases, titrable acidity decreases and peel color changes from green to greenish yellow to yellow (Nambi et al., 2016; Vélez-Rivera et al., 2013). Such variations can be analyzed for ripeness estimation. Near infrared spectroscopy can also be utilized for ripeness based analysis (Rungpichayapichet et al., 2016). Most of research works have utilized mango peel color properties for ripeness determination. RGB color space, HSV space, CIELab space, YIQ space etc are few of the color space models that are commonly used for color based analysis. RGB is the most commonly used color model, however other models have helped in achieving improved color based classification. Models like HSI, HSV, CIEL*a*b* separate the brightness component from color component which helps in better color feature extraction. Ripeness based research works have been divided according to color space models, as those utilizing single color models and those exploring multiple color spaces. Non-color based ripeness determination approaches are also discussed.

RGB color space

RGB (red-green-blue) is a device dependent color space which represents color in terms of three primary colors. Ripeness based analysis based on RGB color model has not gained very good results (Nandi et al., 2016; Limsripraphan et al.,2019). However, RGB color properties when utilized with other color spaces have improvised the ripeness related classification results. Nandi et al. (2016) predicted the shelf life(actual-days-to-rot) of mangoes using Support vector regression using 27 RGB features. 200 images of five different mango varieties were considered which resulted in accuracy of 83.9%, comparable with manual expert based technique. Limsripraphan et al. (2019) concluded that red channel of RGB color space was significant in classifying mangoes into two stages- Ripe and Unripe. Binary classification on (COFILAB Kent) dataset achieved an accuracy of 90% with Bayesian classifier and 83% with SVM classifier. Nambi et al. (2016) classified mangoes into five ripening stages based on 18 NDI (Normalized differential index) and area features extracted from RGB image. Hierarchical clustering was applied to create a labelled dataset of 114 mangoes based on measured physio-chemical, color and texture properties. Quadratic discriminant analysis was employed on the NDI and area features to achieve misclassification rate of 7.9% and 3.5% respectively.

CIEL*a*b* color space

The CIEL*a*b* expresses color using three components namely L*- lightness, a* and b*-chromatic coordinates. CIEL*a*b* color properties provide better color analysis and have resulted in good ripeness based classification results. Naik et al. (2015) explored La*b* color space for three stage ripeness classification. Mean of a channel and b channel were extracted from image. Fuzzy classifier was employed on 900 Kesar mango images, gaining an accuracy of 93.5%. Nagle M. et al. (2016) developed a computer vision based system for determining peel color variations in 375 Thai mangoes during ripening process. Prediction models were built and correlation between CVS and other color measurement techniques was studied. A three stage maturity classification based on yellowness index, computed from CIE chromatic values gained an accuracy of 72% - 92% for Nam Dokmai and 98% - 100% for Maha Chanok. Simple threshold based ripeness classification was performed using a channel which gained accuracy of 98.88% (Pandey et al., 2014b).

HSI color space

HSI color space expresses color in terms of three components, hue, saturation and intensity. HSI color space features have proven to be strong in classifying mangoes into five ripeness stages. Mean hue and mean saturation values computed from HSI color space could correctly predict mango ripeness with an accuracy of 96.47% (Bermudez et al., 2013).

Multiple color spaces

Ripeness based analysis exploring multiple color spaces has resulted in very good results. Mim et al. (2018) explored the RGB and HSI color models to classify mangoes into 6 ripening stages using a decision tree classifier. 24 color features related to RGB and HSI channels were extracted. Four most relevant features were identified using best first search method and information gain based ranker search method. Vélez-Rivera et al. (2013) in their work performed a detailed analysis of mango ripeness using physiochemical and color features. TSS, TA and firmness were used to calculate the ripeness index. Color features namely L*, a*, b*, H, S, and B were extracted from the CIELAB and HSB color spaces. Correlation between TSS, TA, firmness, RPI, L*, a*, b*, H, S, and B was studied. Results showed a strong correlation between features except for L* and B. Multivariate Discriminant Analysis classification of 117 fruit images with all 8 significant features resulted in accuracy of 100%.

Non color based approaches

Rungpichayapichet et al. (2016) explored the significance of near infrared spectroscopy as ripeness indicator. Partial least squares regression model was built to predict TSS, TA, firmness and RPI from mango spectral data. Strong correlation was observed between NIRS and physio-chemical properties especially TSS. A performance comparison of four CNN models (Inception v4, Xception, ResNet50, and MobileNet) for three stage ripeness classification was done Naik (2019b). Feature extraction was performed using CNN and SVM was used for classification. MobileNet achieved best accuracy of 82.04%. Sahu and Potdar (2017) determined mango maturity using shoulder fullness parameter. Shoulder fullness was identified using mangoes contour line information. Khalid et al., (2017) utilized the correlation between specific gravity and ripeness stages. Actual specific gravity determined using traditional Archimedes' principle was found to similar to one computed using image based techniques. A summary of mango ripeness classification works has been presented in Table 2.

Table 2: Ripeness Based Analysis Summary

Ref	Color Spaces	Classifier	Stages	Result(Accuracy)
Nambi et al. (2016)	RGB	LDA and QDA	5	E^e: 7.9% & 3.5%
Limsripraphan et al. (2019)	RGB	Naïve Bayes and SVM	2	90% & 83%
Mim et al. (2018)	RGB and HSI	Decision tree	6	96%
Naik (2019b)	No color: Direct CNN	CNN	3	82.04%
Vélez-Rivera et al. (2013)	CIELAB, HSB	Multivariate Discriminant Analysis	3	90.6%
Naik et al. (2015)	CIEL*a*b*	Fuzzy	3	93.5%
Nandi et al. (2016)	RGB	Support vector regression	-	84%
Bermudez et al. (2013)	HSI	Naïve Bayes	5	96.47%
Rungpichayapichet et al. (2016)	No color: NIR Spectral data	Discriminant analysis	4	More than 80%
Nagle M. et al. (2016)	CIELAB	Simple classification based on yellowness index ranges	3	72-92% & 98%-100%
Pandey et al. (2014b)	CIELab (a* channel)	Simple thresholding	2	98.88%

e: Error rate

SIZE BASED ANALYSIS

One of the most vital appearance based properties while grading fruits is its size. It influences many important marketing decisions. Many times, mango grading standards specify ranges related to mango size. Generally, mango size based grading is done based on mango weight, however many attempts have been made for image based size estimation. Various geometrical properties such as fruit area, perimeter, length, breadth etc can be calculated from mango image and used for size based classification. Mango shape is closest to an ellipse. Hence most of researchers have used ellipse fitting algorithms to compute the geometrical properties.

Naik (2019b) compared performance of four CNN (Convolutional Neural Networks) models for a three category, size based classification. Analysis was carried out using 1188 Kesar mango images. MobileNet performed best with accuracy of 72.46%. A three category fuzzy classification using mango weight and area. conducted on 900Kesar mango images achieved an accuracy of 96% (Naik et al., 2015). Behera et al. (2018) conducted on-tree size estimation of mango fruits, thus each image had multiple mangoes. Randomized hough tansform was used for mango detection. Comparison of mango area computed using image extracted major-minor axis and manually measured length-width was performed. A computation of mango size from mango image, by counting number of pixels along major and minor axis was done. The computed length was found to be approximately equal to actual length, only with an average error within 3%Nandi et al. (2016). Pandey et al. (2014a). performed size based classification of healthy mangoes into three categories (poor, medium and excellent). Mango area and diameter of 58 healthy mangoes were fed to a fuzzy classifier which achieved an accuracy of 91.41%. An attempt to develop image processing system to perform size based sorting using geometrical features like ferret diameter, projected area, perimeter and roundness was made. Initial labelling was done based on mango weight and relationship between weight and geometrical features was studied. It was observed that ferret diameter, perimeter, area could successfully classify mangoes into three grades. Roundness couldn't achieve good size classification. Momin et al. (2017). Rojas-Cid et al. (2018) designed a size based hardware and software mango sorting system. A calibration chart was created which gave relationship between caliber (size category), weight and number of pixels (mango area). Area was computed and mango was classified according to the developed chart. Experiments carried out on 62 mangoes and it took 3.75 sec to classify each mango. Pandey et al. (2014b) classified mangoes into four categories (poor, medium, good, excellent) using major and minor axis extracted from mango image. Ellipse fitting was used to determine the axes length. Fuzzy classification was performed on 517 images. Ibrahim et al. (2016) performed mass estimation of mangoes from its estimated volume using elliptic cylindrical disk method. A high correlation was found between image estimated volume and actual mass. Mass based grading into four classes could achieve recognition rate of 94% A summary of size based analysis has been given in Table 3.

Table 3: Size Based Analysis Summary

Ref	Features	Classifier	Result (Accuracy)
Naik (2019b)	Extracted by CNN	Support Vector Machines	72.46%
Naik et al. (2015)	Area, weight	Fuzzy	96%
Pandey et al. (2014a)	Diameter and area	Fuzzy	91.41%
Alejandro et al. (2018)	Area	Probabilistic neural network	87.5%
Behera et al. (2018)	Area using major and minor axis	-	E^e: 3.07%
Nandi et al. (2016)	Major and minor axis	-	97%
Momin et al. (2017)	Projected area, ferret diameter	Simple range based classification	97%
Rojas-Cid et al. (2018)	Projected area	Calibration chart	89.5%
Pandey et al. (2014b)	Major and Minor axis	Fuzzy	96.58%
Ibrahim et al. (2016)	Image estimated volume	-	94%
Sa'ad et al. (2015)	Image estimated weight	-	95%

e: Error rate

DEFECT BASED ANALYSIS

Rot, bruises, sunburns, rubbing defects are some of the common defects that can occur in mangoes. Such defective mangoes should be identified and discarded based on defect level. Some mango grading standards specify the level of defect allowed in every grade. Mango defects directly affect its physical appearance and leads to decreased customer satisfaction. Hence defect based mango classification is essential. Defects can be easily identified from mango image using proper image processing methods. A threshold applied on appropriate color space component can help in defect segmentation. Defective area and then be calculated and defect ratio be determined. Mangoes are then classified according to computed defect ratio.

Most of research works apply this methodology for defect analysis (Ganiron Jr et al., 2014; Sahu and Potdar, 2017; Patel et al., 2019).Some of the researchers perform defect based fruit classification using texture analysis. Texture properties are extracted using gray level co-occurrence matrix and machine learning clarifier is used to identify defective fruits (Capizzi et al. 2015). A summary of defect based analysis is presented in Table 4.

Table 4: Defect Based Analysis Summary

Ref	Technique	Classifier	Result(Accuracy)
Ganiron Jr et al. (2014)	Thresholding Cb (YCbCr)	Defect ratio based classification	-
Pandey et al. (2014a)	Thresholding b* (CIELa*b*)	Defect ratio based classification	93.33%
Nandi et al. (2016)	Thresholding R-B, G-B	Defect ratio based classification	90%
Patel et al. (2019)	Thresholding H (HSL)	Defect ratio based classification	88%
Thendral et al. (2016)	Texture-GLCM, color (HSV, YIQ)	Auto associative neural network	94.5%
Limsripraphan et al. (2019)	Thresholding- gray scale	Defect ratio based classification	85%
Bermudez et al. (2013)	Thresholding- S channel (HSI)	Defect ratio based classification	90.66%
Sahu and Potdar (2017)	Defect ratio - Contour detection	Defect ratio based classification	-
Capizzi et al. (2015)	Color, Texture, Shape	Radial bias probabilistic neural network	E[e]: 2.75%
Pandey et al. (2014b)	Histogram Lab (b* channel)	Defect ratio based classification	96.95%

e: Error rate

Ganiron Jr et al. (2014) performed mango grading based on roundness and defect. The RGB image was converted to YCbCr color space and fixed thresholding was applied on Cb channel to identify defects. Percentage defect was then calculated and combined with roundness to classify mangoes into three grades (export, local and reject). Sahu and Potdar (2017) performed defect identification of mangoes using edge detection and contour filling. Experimentation was carried out on 28 mangoes from (COFILAB Kent). Pandey et al. (2014a) classified mangoes as healthy and defective based on b* component of CIEL*a*b* color space. It was observed that color of mango diseases is generally black or brown. Ranges for b* value for healthy and defective pixels was determined from histogram analysis and dominant density range method was used for classification. Nandi et al (2016). explored the RGB color space for defect detection. They observed that blue value is high in defective pixels, hence difference of mean R, G and G, B were used to determine the defective and healthy pixels from apex to stalk along longitudinal axes. Patel et al. (2019) performed a series of image processing operations like color plane extraction, threshold setup, image equalization, morphological operations, binary inversion etc. to find the amount of defects from mango image. Hue plane from HSL color space was explored and thresholding was applied. According to amount of defect present, mangoes were classified into four categories namely slight defect, moderate defect, severe defect and shriveled defects. Images acquired in two mango postures (0 and 180 degrees) were utilized. Experiments were performed using 180 mango fruits and accuracy, efficiency and processing time were analyzed. It was observed that accuracy and efficiency go on decreasing as defect severity increases. Limsripraphan et al. (2019) performed surface defect detection using image labelling technique and defect spot extraction. Defect analysis conducted on 54 ripe and 46 unripe mango images resulted in accuracy of 85%. Bermudez et al. (2013) in their work classified mangoes into four defect categories namely very mild, mild, medium and high. Thresholding on S channel of HSI color space was performed for spot estimation. Pandey et al. (2014b) implemented defect classification using thresholding on b* channel of CIELab color space. Ranges for b* value of diseased and healthy pixels were defined using histogram analysis and dominant density range method was used to find defect ratio. Classification of 524 mangoes into two categories could achieve accuracy of 96.95%. Capizzi et al. (2015) performed five category defect based classification of 400 oranges. Texture features using gray level co-occurrence matrix, color features and shape features were extracted from orange image and analyzed using Radial bias probabilistic neural networks. Oranges were classified as normal, surface defect, morphological defect, color defect and black mould. Overall error rate of 2.75% was achieved. Thendral et al. (2016) designed a system for skin defect identification for orange fruits. Image segmentation was performed using saturation and intensity components. Forty-four second order features based on GLCM (Gray level co-occurance matrix) and six color features related to HSV and YIQ components were extracted. Feature selection was performed using wrapper based genetic algorithm. Performance of SVM, back propagation neural network and auto associative neural network for binary classification (defective, non-defective) of oranges was analyzed.

SHAPE BASED ANALYSIS

Deformed mangoes usually lead to decreased customer satisfaction, thus shape based mango sorting is essential. Many researchers have attempted shape based mango classification using image processing techniques. Geometrical features like eccentricity, extent, cross ratio, roundness can be utilized for shape determination. One of the most commonly used method for shape analysis giving best results is Fourier descriptors. Fourier descriptors can be extracted from binary mango image obtained after segmentation and given as input features to machine learning classifier. Shape based analysis summary is given in Table 5.

Table 5: Shape Based Analysis Summary

Ref	Features	Classifier	Result (Accuracy)
Sa'ad et al. (2015)	Fourier descriptors	SVM	100%
Naik et al. (2015)	Eccentricity, extent, cross ratio	Fuzzy	92%
Naik (2019b)	Extracted by CNN	SVM[a]	91.78%
Nandi et al. (2016)	Fourier descriptors	SVM[a]	91%
Ibrahim et al. (2016)	Area Ratio, Fourier descriptors	Fishers Linear Discriminant function	92%

a:SVM: Support Vector Machines

Sa'ad et al. (2015) performed three category shape classification using centroid based Fourier descriptors extracted from mango image. It was observed that three grades could be easily characterized using 3rd harmonic of Fourier descriptor. Performance of discriminant analysis and support vector machines was compared and SVM achieved better results. Naik et al. (2015) employed eccentricity, extent and cross-ratio properties related to shape for mango classification. Two category fuzzy classification, utilizing three shape properties, performed on 900 Kesar mango images resulted in accuracy of 92%. Naik (2019b) compared performance of four CNN models for shape classification. All four CNN models achieved good results for shape classification as compared to size and maturity. 728 mango images were used for training and Inception v4 gave best results. Nandi et al (2016). utilized centroid based Fourier descriptors for three category shape classification. Support vector machine was used as classifier and it was observed that mangoes could be best classified by third harmonic component $|F(3)|$.

Ibrahim et al. (2016). extracted size-shape parameters namely area-ratio, aspect-ratio, roundness and Fourier descriptors from mango image. First ten harmonics of Fourier descriptor were used to calculate parameters S1, S2 and S3. Stepwise discriminant analysis selected area-ratio, S1, S2 and S3 as best features which classified training set mangoes with accuracy of 98.3%. Classification functions were further created based on Fisher's linear discriminant functions. Shape analysis performed on 140 mangoes using these linear equations could achieve accuracy of 98.4% for regular and 85.7% for misshapen mangoes.

MULTI-PARAMETER BASED GRADING

Many research works utilize more than one parameter for grading. Mango grade a determined based on multiple parameters together. Government specified grading standards or any export grading standards can be utilized to determine these grades (Agmark standards). Usually image processing and machine learning techniques are first applied to determine the mango category according to each parameter. Such parameter-specific results are then given as input to machine learning model to determine the mango grade. A summary of integrated grading is given in Table 6.

Table 6: Multi-Parameter Based Mango Grading

Ref	Parameters	Classes	Classifier	Result (Accuracy)
Naik (2019b)	Size, Shape, Ripeness	Class 1,2,3,4	CNN, SVM, decision making	83.97%, 70.04%
Agilandeeswari et al. (2017)	Geometric, Textural, Histogram	Good, very good, bad	SVM	97%
Nandi et al. (2016)	Size, shape, defect, maturity	G1, G2,G3,G4	Fuzzy	88%
Naik et al. (2015)	Shape, size, maturity	Class 1,2,3	Decision making	90%
Ganiron Jr et al. (2014)	Size, defect, roundness	Export, local, reject	KNN	-
Yossy et al. (2017)	Maturity, size	large-ripe, large-unripe, small-ripe and small-unripe	ANN	94%
Balbin et al. (2017)	Size, Color	Export, class1, class2	Decision making	-
Pandey et al. (2014b)	Size, defect, maturity		Fuzzy	97.47%
Alejandro et al. (2018)	Area, color, black spots	Extra-class (small, medium, large), others	Probabilistic neural network	87.5%

Naik (2019b) graded mangoes in 4 classes based on size, maturity and shape features. Dataset prepared in Naik et al. (2015) was used after augmentation to create 2432 images. Two deep learning approaches were applied and performance analysis of four CNN models namely Inception v4, Xception, ResNet and MobileNet was done. In both approaches MobileNet performed excellent with highest accuracy and fastest execution time. Agilandeeswari et al. (2017) sorted mangoes into three classes namely-good, very good and bad using multiclass SVM. Geometric features (area, eccentricity, perimeter, major axis, minor axis), textural features (GLCM features) and histogram features (mean, skewness, kurtosis) were extracted from mango image and feature selection was performed using firefly algorithm. SVM classification implemented on (COFILAB Kent) dataset from COFILAB achieved an accuracy of 97%. Nandi et al. (2016) performed classification of mango fruits based on maturity and quality score. 200 mango images of 5 varieties was collected and pictures were taken daily for 20 days in order to observe ripeness stages. Maturity was determined in terms of actual days to rot, based on color features, using support Vector Regression. A quality score was assigned to each mango depending on size, shape, surface defects using multi attribute decision making. Finally based on maturity and quality score, a fuzzy rule based classifier was applied to grade mangoes in 4 categories. Naik et al. (2015) classified Kesar mangoes depending on its shape, size and ripeness properties. A dataset of 900 images, 300 mangoes with 3 angles was prepared (Naik, 2019a). Shape classification was done using eccentricity, extent and cross ratio. Area and weight features utilized for size classification. Maturity prediction was done using Lab color analysis. Three category grading based on all three parameters resulted in average accuracy of 90% and grading time of 2.1 sec. Ganiron Jr et al., (2014) graded mangoes into three qualities namely export, local and reject based on its roundness and percent defect. Roundness was computed from area and perimeter. Defect was identified using simple thresholding on Cb color component. Yossy et al. (2017) implemented Gincu mango classification using two parameters, size and ripeness. Color analysis was performed in HSV space and size analysis through contour detection. Each image is represented as 257 feature vector, first 256 elements for color and 256th element value for size. This array given as input to neural network. ANN training performance using 52 mango images and different number of hidden layers was analyzed. Classification done into 4 categories achieved an accuracy of 94% with 40 hidden layers. Balbin et al., (2017) graded mangoes into three classes according to United Nations Economic Commission for Europe’s (UNECE) standard. Color and size of mango were used to decide its quality. Series of image pre-processing operations were performed and RGB pixels values were analyzed. Height and width of mango were extracted from image for size estimation. Pandey et al. (2014b) classified mangoes based on size, maturity and defects. 600 mangoes belonging to 4 different varieties were used. Defect, size and maturity based classification achieved accuracy of 96.95%, 96.58% and 98.88% respectively, while integration of overall system resulted in an accuracy of 97.47%. Alejandro et al. (2018) classified mangoes into four categories based on area, color and black-spots using probabilistic neural network. An attempt was made to compute mango weight from mango pixel area.

CONCLUSION

Mango grading is an important post-harvest process which provides quality assurance and thereby increases customer satisfaction. External features like mango size, shape, ripeness and defect can be extracted from mango image using image processing techniques. Machine learning models can then be applied to features to classify mangoes into different grades. In this paper a detailed analysis of appearance based mango grading is performed and parameter-wise survey is presented. From the above study it can be concluded that ripeness analysis based on HSV, HSI and CIELab color models have gained better accuracy than RGB color model. Geometrical features namely area, major axis, minor axis gives better size based classification. Defects can be successfully segmented using thresholding techniques and shape classification is best achieved using Fourier descriptors. Many machine learning models have been utilized for classification, however SVM and Fuzzy classifiers tend to perform better. Thus image processing and machine learning techniques can be successfully applied to extract mango ripeness, size, shape and defect parameters. Such image extracted parameters when used for grading can help Space error accurate, reliable and consistent mango grading.

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