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A Survey: Fruit Classification Using Machine Learning

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Abstract- One of the important quality features of fruits is its appearance. Appearance not only influences their market value, the preferences and the choice of the consumer, but also their internal quality to a certain extent. Color, texture, size, shape, as well the visual flaws are generally examined to assess the outside quality of fruit. Manually controlling external quality control of fruit is time consuming and labor-intensive. Thus for automatic external quality control of food and agricultural products, computer vision systems have been widely used in the food industry and have proved to be a scientific and powerful tool for by intensive work over decades. The use of machine and computer vision technology in the field of external quality inspection of fruit has been published based on studies carried on spatial image and / or spectral image processing and analysis. A detailed overview of the process of fruit classification and grading has been presented in this paper. Detail examination of each step is done. Some extraction methods like Speeded Up Robust Features (SURF), Histogram of Oriented Gradient (HOG) and Local Binary Pattern (LBP) are discussed with the common features of fruits like color, size, shape and texture. Machine learning algorithms like K-nearest neighbor (KNN), Support Vector Machine (SVM), Artificial Neural Networks (ANN) and Convolution Neural Networks (CNN) are also discussed. Process, advantages, disadvantages, challenges occurring in fruit-classification and grading is discussed in this paper, which can give direction to researchers.

Keywords- Fruit, Classification, Grading, Machine and Computer Vision.

1. INTRODUCTION

India is an agricultural country. International comparisons reveal the average yield in India is generally 30%-50% of the highest average yield in the world. Agriculture has comprised of 16.5% GDP by sector (2016 est.) with approximately 50% labor force (2014 est.) and 10% total export. The budget 2017-18 pitched for more reforms in agriculture sector and increased funds for almost all areas of agriculture [1]. India exported $39 billion worth of agricultural products in 2013, making it 7th largest agricultural exporter worldwide. According to 2010 FAO, India is world's largest producer of many fresh fruits and vegetables, milk, major species, jute, millet and castor oil seeds. India is world's second largest producer of wheat and rice. India is world's second or third largest producer of several dry fruits, agriculture based textile raw materials, roots and tuber crops, pulses, farmed fish, eggs, coconut, sugarcane and numerous vegetables [2]. Analyzing the vision is a general characteristic of our brain. Our brain takes no effort to read and understand a sign, or separate a lion and a jaguar, or recognize people by their face. All this is too simple for humans. Whereas for computers these are the actual difficulties to solve. Due to advancement in vision based computing capabilities and as algorithms can understand images and videos, systems can be prepared now which understand what we are looking at and what actions we need to perform [3]. Many machine vision algorithms are available for agricultural applications too [4, 5, 6]. These algorithms are used frequently for speed, economic benefits and proper inspection, measurement and evaluation tasks. For acquiring a variety of information from the farms, such as fruit and vegetable detection, estimation of fruit size and weight, fruit and vegetable identification, leaf area and yield estimation, plants, classification and grading, computer vision algorithms are often used for it, autonomous Selective sprayers used and much more [7]. Among the above, fruit classification and fruit grading is one of the most important and difficult task as in the supermarket the cashiers need to know the different categories of a fruit element to determine its price [7]. In order to reduce the manual work of classification and sorting to improve the quality of the fruit grading, we can use the image processing and machine learning algorithms. Shape of the fruit, color and size can be extracted to obtain a non-destructive type of fruit classification and gradation. Machine classification and grading can be carried out automatically if some standard rules for grading criteria are made. Automatic sorting system that can perform fast, save time and reduce manual labor can be used because it has a higher priority because of the ever-growing need for high-quality fruit. Many automatic classification and sorting systems are available for various fruits such as citrus fruits, orange apples, oil palm fruits, strawberries, mangoes, lemons, dates, etc. [8, 9, 10, 11]. Parameters of non-destructive fruit classification and grading are composition, defects, size, shape, strength, flavor and color. Maturity indices for fruit grading such as flesh color, skin color and specific gravity may also be included therein (the ratio of the mango density to the density of the water)[12]. The basic steps of the automatic image-based fruit grading are: fruit image recognition, fruit object recognition, fruit classification, and finally grading by quality estimation. The parameters of the fruit grading and the weighting of each parameter are changed depending on the type of fruit. So you first have to identify the type of fruit and then decide the parameters before the grading. Fig. 1 shows the proposed model for the classification of mango fruits and their grading [11]. The same applies to all fruits. Grading standards are amended on the basis of affected persons. It is possible that the area of small Rajapuri mango can be more than the large Dashehari mango. So, before we make the grading, we need to make fruit classification and take fruits into account.

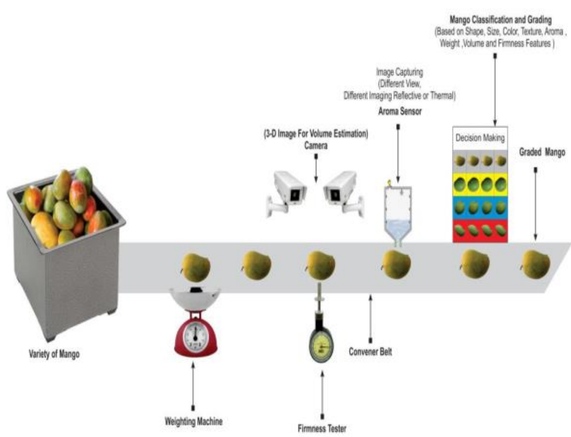

Figure 1: Proposed model for fruit classification and grading system

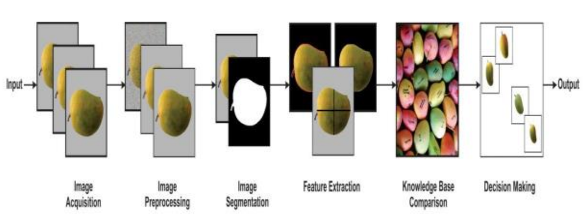

Figure 2: Flow of fruit classification and grading process

2. FRUIT CLASSIFICATION AND GRADING PROCESS

In the fruit grading process image acquisition and pre-processing, segmentation, feature extraction, knowledge base comparison and decision making steps are involved. These steps are shown in Figure 2.

2.1 Image Acquisition and Pre-processing

First the image of the fruit is taken by any image capturing device. For doing so, 3 computer vision systems are most widely used in the external quality inspection of food and agricultural products, which are Traditional, Hyper spectral and Multispectral Computer Vision Systems [13].

Preprocessing methods use a small neighborhood of a pixel in an input image to obtain a new brightness value in the output image. Such preprocessing operations are also named filtration. Local preprocessing methods can be divided into the two groups according to the goal of processing: smoothing suppressed noise or other small fluctuations in the image; equivalent to the suppression of high frequencies in the frequency range. Unfortunately, the sharp edges also smoothed important information about the picture. Gradient operators are based on local derivatives of image function. Derivatives are larger at the locations of the image where the picture function changes rapidly. The goal of the gradient operators is to display such places in the picture. Gradient operators suppress low frequencies in the frequency domain (i.e., they act as a high-pass filter).

2.2 Image Segmentation

In image processing, image segmentation can be defined as a "process of partitioning a digital image into multiple segments" (sets of pixels, also referred to as super pixels). The goal of image segmentation is to simplify and / or change the representation of an image, which is more meaningful and easier to analyze. Image segmentation methods are categorized on the basis of two properties of discontinuity and similarity. Methods based on discontinuities are called boundary-based methods, and methods based on similarity are called region-based methods. The output of the segmentation is either a limitation of the object from the background or the region itself. In the color image segmentation, different color spaces such as RGB, HSI and CIELab are used [14], with the image segmentation. Some of the segmentation methods are listed in fig. 3 as follows [10].

2.3 Feature Extraction

Feature extraction is a low-level image processing application. For a picture, the feature is the "interest" part. In the pattern recognition literature, the name feature is frequently used to designate a descriptor. Repeatability is the desirable property of a feature detector. After image segmentation, the next step is to extract image features useful in describing fruits. Various features can be extracted from the image: color, shape, size, texture. There are some local feature detector and visual descriptor, which are used for object recognition and classification. Some of them are Speeded Up Robust Features (SURF), Histogram of Oriented Gradient (HOG) and Local Binary Pattern (LBP). All these features, feature detectors and visual descriptors are explained in next section.

2.4 Knowledge-based comparison and decision making

The comparison of the extracted features from the image takes place with the predetermined classification and sorting criteria or the rules. The features are compared on the basis of the extracted features and classification is made as well as grades are given to the fruits. The knowledge-based comparison and decision-making can be done using machine learning algorithms. Some of the machine learning algorithms are Decision Tree, Regression (simple, multiple, polynomial, logistic), K-nearest neighbor (KNN), Support Vector Machine (SVM), Fuzzy Logic, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) or Artificial Neural Networks (ANN). Some of these algorithms are explained in section 4. This is the final step of the classification and grading process. Hence all the above steps comprise the fruit classification and grading process.

3. FEATURE EXTRACTION TECHNIQUES

Next step in fruit classification and grading process after segmentation is feature extraction. Main and important visual external features for fruit are its color, size, shape and texture. Feature descriptor is a representation of an image or part of it, which extract useful information and discards unnecessary information. It is mainly used for image recognition and object detection. In this section, we have briefly discussed all. Some of the feature descriptors used to detect and recognize object are SURF, LBP and HOG. We have discussed these feature descriptors also here in brief.

3.1 Color Feature Extraction

As color is most visually striking feature of any image it pays an important role in classification and grading system and also to identify defective fruits from normal fruits. Most of the existing system defines maturity of fruits by comparing its color with the existing predefined reference colors. Color models are divided into several models like HIS, HSV, JPG, L*a*b*, GALDA, RGB, sRGB, etc. Detail list of these color model are describe in [15, 14]. Color feature extraction methods are widely used in agriculture applications and specifically in fruit classification and grading process. Color models like RGB, HIS and L*a*b* are used with different methods like dominant histogram, mean of color channels, etc.

Color features extraction methods broadly fall in two categories:

1. Global methods (global color histogram, histogram intersection, image bitmap)

2. Local methods (local color histogram, color correlogram, color difference histogram)

Detail description of color feature extraction is given in [16]. 2D colors histograms are used to find co-occurrence frequency and back projecting is applied to evaluate Date fruit maturity and quality in [17]. Review of different segmentation techniques, color models and feature extraction methods for fruit disease detection and fruit grading is discussed in [18]. Mango fruit sorting is performed in [19] using Gaussian Mixture Model and Fuzzy logic by considering maturity and size as parameters. 88% to 92% results are achieved for different maturity level. For orange fruit defect classification, color and texture features with novel radial basis probabilistic neural network is used and 88% accuracy is achieved in [20]. Intra class fruit classification with color and texture features is performed in [21] where ANN is used and 83-98% accuracy is received. [22] presents fruit recognition method based on color and texture feature. For color feature extraction, some of the Python functions are available at *skimage.color*. Some functions are *rgba2rgb(), skimage.util.invert(), label2rgb(), skimage.exposure.histogram(), rescale_intensity()* and *equalize_hist().*

3.2 Size feature extraction

Fruit size is also one the most important parameter to measure the quality of fruit, larger the fruit, better it is. Larger fruits attract even more prices. It is difficult to measure fruit's size due to its natural irregularities. For size feature extraction, different size measures, which are most commonly used, are area, perimeter, weight, height (length), width and volume. Some other measures for size feature extraction are radius, equatorial diameter, and major and minor axes.

Applications of size inspection are one of the important parameter of fruit's quality measurement. It is explained in detail in [13]. Detailed review of non-destructive methods for fruit as well as vegetable for size determination is conducted in [23]. Weight, volume, analytical methods, asymmetrical method and statistical method are briefly explained for size estimation in [24]. For automatic examination and quality assessment of fruits and vegetables, size and volume estimation methods are described in [25]. [26] Performs Date fruit classification. For the same shape and size feature with texture descriptor are used where shape and size are measured using fitting object to ellipse. Non-destructive mango fruit grading with maturity and size (area) features has been performed in [27] where thermal imaging using FLIR One camera was used. Length, maximum width, and maximum thickness are used with simple linear regression (SLR), multiple linear regression (MLR) and artificial neural network (ANN) to estimate size-mass of mango fruit in [28], where accuracy and success rate of 96.7% is achieved. Length, maximum diameter of the equatorial section, and projected area is used with stepwise multiple linear regression method to classify kiwifruit in [29]. Here accuracy reaching 98.3% by proposed method. For size feature extraction of labeled region, below is the Python function.

3.3 Shape feature extraction

While purchasing fruit as well as for classification and grading, shape is considered very important. The objective of the shape description is characterize the shape in such a way that the values are very similar objects in the same form class or category, and quite different for objects in different categories. This is known as the uniqueness condition. Besides the uniqueness and invariance to affine transformations, namely translation, rotation, scaling, others desirable property of any shape description method is non-ambiguity or completeness [30].

Size dependent measurements of shape include compactness, elongation, convexity, roughness, etc. while size-independent measurements of shape includes region-based (statistics of pixel’s spatial information) and boundary-based (Fourier transform, discrete wavelet transform, autoregressive models, etc.). Some of the shape descriptors and techniques are explained in brief in [24].

Multiple appearances with color, shape and size feature are used for identification of Strawberry cultivar and its quality evaluation in [31] where classification is increased to 68% compared to single feature. In [32], local binary pattern (LBP) or weber local descriptor (WLD) histogram with Fisher discrimination ratio (FDR) based feature selection is used for shape-size and texture based Date fruit classification and achieved 98% classification accuracy. Color histogram, texture and shape features used with PCA, fitness-scaled chaotic artificial bee colony (FSCABC) algorithm and feed forward neural network (FNN) to classify fruits in [33]. Accuracy achieved is 89.1%. [34] Reviews of different fruit grading systems and parameters are discussed in detail. Fourier-descriptor is used for shape feature extraction with SVM to classify mangoes and has achieved almost 100%.

4. LITERATURE REVIEW

Digital image processing, as a computer-based technique, has been extremely used by scientists to solve problems in agriculture. Fernando et al (2010) built a system to diagnose six different types of surface defects in citrus fruits using a multivariate image analysis strategy. Images were unfolded and projected onto a reference eigen space to arrive at a score matrix used to compute defective maps and 94.2% accuracy was reported. Cho et al. (2013) used hyperspectral fluorescence imaging for detecting cracking defects on cherry tomatoes while Omid et al. (2013) used shape, texture and color features to sort tomato fruits according to their circularity, size, maturity, and defects. They achieved 84.4% accuracy for defect detection using a probabilistic neural network (PNN) classifier. Chowdhury et al. (2013) have recognized 10 different vegetables using the color histogram and statistical texture features. They have gained the classification accuracy up to 96.55% using a neural network as a classifier. Danti et al. (2012) classified 10 types of leafy vegetables using BPNN classifier with a success rate of 96.40%. They first cropped and resized the image and then extracted the mean and range of hue and saturation channel of HSV image to form the feature vector. Suresha et al. (2012) have achieved 95% classification accuracy over a dataset of containing 8 types of different vegetables using texture measures in RGB color space. They have used watershed segmentation to extract the region of interest as a pre-processing and decision tree classifier for training and classification purpose. Omid et al. (2013) used shape, texture and color features to sort tomato fruits according to their circularity, size, maturity and defects. They achieved 84.4% accuracy for defect detection using a probabilistic neural network (PNN) classifier. Color, texture and shape features have been evaluated for fruit defect detection system, also in conjunctions with PNNs.

Dubey & Jalal (2012a cited in Dubey & Jalal 2013) proposed a framework for recognizing and classifying fruits and vegetables. They considered images of 15 different types of fruit and vegetable collected from a supermarket. Their approach was to first segment the image to extract the region of interest and then calculate image features from that segmented region which was further used in training and classification by a multi-class support vector machine. They also proposed an Improved Sum and Difference Histogram (ISADH) texture feature for this kind of problem. From their results, ISADH outperformed the other image color and texture features.

Haiguang et al. (2012) classified two kinds of wheat diseases based on color, shape and texture features to train a back propagation neural network. The resulting system achieved a classification accuracy of over 90%. Arefi et al (2011) developed a segmentation algorithm for the guidance of a robot arm to pick the ripe tomato using image processing technique. To reach this aim, they prepared a machine vision system to acquire images from a tomato plant. Their algorithm works in two phases: (1) background subtraction in RGB color space and then extracting the ripe tomato considering a combination of RGB, HSI, and YIQ color spaces and (2) localizing the ripe tomato using morphological features of the image.

Fruit	Features	Classifiers	Accuracy (%)	References
Mango	Maturity, Size	Fuzzy,Thermal Imaging	90	S. Naik et. al. 2017
	Size, Volume	MLR, ANN	96.7	K. Utai et. al. 2015
	Shape, Weight	FD, DA/SVM/Weight	98.3/100/95	F.S.A. Sa'ad et. al. 2015
	Color, Size	GMM	88.3-90.5	C. S. Nandi et. al. 2014
	Color, Fractal Analysis	LS-SVM	Up to 100	H. Zhang, 2012
Tomato	Color, Texture	PCA, SVM	92	N.A. Semary et. al., 2015
	Color, Texture, Shape	PNN	84.4	O. O. Arjenaki, 2013
Orange	Color, Texture	ANN	88	G. Capizzi et. al., 2016
Apple	Color, Size	Naïve Bayes	91	M. Ronald et.al., 2016
Kiwi	Shape	MLR	98.3	L. Fu. et. al., 2016
Strawberry	Color, Size, Shape	Cluster Analysis, Multidimentinal Scaling,DA	>68	K. Yamamoto et. al., 2015

Table 1: Summary of fruit classification and grading methods

They achieved accuracy up to 96.36% on 110 tomato images. Haidar et al. (2012) presented a method for classification of date fruits automatically based on pattern recognition and computer vision. They extracted appropriately crafted a mixture of 15 different visual features, and then, tried multiple classification methods. Their performance ranged between 89% and 99%. Cho et al. (2013) used hyperspectral fluorescence imaging for detecting cracking defects on cherry tomatoes. Omid et al. (2013) used shape, texture and color features to sort tomato fruits according to their circularity, size, maturity and defects. They achieved 84.4% accuracy for defect detection using a probabilistic neural network (PNN) classifier. Danti et al. (2012) classified 10 types of leafy vegetables using BPNN classifier with a success rate of 96.40%. They first cropped and resized the image and then extracted the mean and range of hue and saturation channel of HSV image to form the feature vector. Suresha et al. (2012) have reached 95% classification accuracy over a dataset of containing 8 types of different vegetables using texture measures in RGB color space. They have used watershed segmentation to extract the region of interest as a pre-processing and decision tree classifier for training and classification purpose.

6. CONCLUSION

External properties of fruits like color, size, shape, texture and different defects are very important attributes of fruits for classification and grading. Now a days due to advancement in machine vision and availability of low cost hardware and software, manual work of fruit classification and grading has been replaced with automated machine vision systems. Other reason of non-destructive automation can be its ability to produce accurate, rapid, objective and efficient results over manual work.

This paper reviews the basic process flow of fruit classification and grading. Feature extraction methods for color, size, shape and texture are explained with SURF, HOG and LBP features. Finally some machine learning approaches like K-NN, SVM, ANN and CNN are briefly discussed. Though some challenges are still need to overcome, but machine vision will prove to be the future for non-destructive fruit classification and grading.

In future, we can work on image classification for local fruits and vegetables. We can also prepare algorithms and machines for fruits and vegetable grading. It can also be used for plants/ leaves/ flowers identification and classification. A system can be develop which will identify plant/leaf/flower and provide information regarding it. We can also work on some more features for grading and classification, which can identify types of disease and/or texture structure of fruits. All these are future direction. One can work on these and prepare prototype model, which can be used in industries. One can even develop mobile applications for the same based on above methods and farmers or general public can use it for identification, classification and grading of horticultural products.

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