International Journal of Engineering Technology and Applied Science

(ISSN: 2395 3853), Vol. 5 Issue 9 September 2019

A Comparative Study of Fruit Recognition System Using Machine Learning Approaches

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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 food. 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 Histogram, Flat box and scatter matrix are discussed with the common features of fruits like color_score, mass, width and height. Machine learning algorithms like Support Vector Machine (SVM), Gaussian Naïve Bayes, Logistic Regression and Decision Tree are also discussed. Process, advantages, disadvantages, challenges occurring in food-classification and grading is discussed in this paper, which can give direction to researchers.

Keywords: - Classification, Features, Mass, Color_score, Width.

I. INTRODUCTION

In agricultural science, images are the important source of data and information. To reproduce and report such data photography was the only method used in recent years. It is difficult to process or quantify the photographic data mathematically. Digital image analysis and image processing technology circumvent these problems based on the advances in computers and microelectronics associated with traditional photography. This tool helps to improve images from microscopic to telescopic visual range and offers a scope for their analysis. Several applications of image processing technology have been developed for the agricultural operations. These applications involve implementation of the camera based hardware systems or color scanners for inputting the images. We have attempted to extend image processing and analysis technology to a broad spectrum of problems in the field of agriculture. The computer based image processing is undergoing rapid evolution with ever changing computing systems. The dedicated imaging systems available in the market, where user can press a few keys and get the results, are not very versatile and more importantly, they have a high price tag on them. Additionally, it is hard to understand as to how the results are being produced.[1]

We have tried to develop a solution which presents classification problem in a most realistic way possible. Apples (malus sp., Rosaceae) are one of the most commonly consumed fruits in the world. In 2011, world apple production was estimated at around 75 millions of tons according to Food and Agriculture Organization stats (15 July 2013). Apples are an important agricultural commodity in the global market for fresh products. The quality of an apple depends on its external characteristics, such as color, size, and surface texture, and internal parameters, such as sweetness, acidity, firmness, tissue texture, ascorbic acid, and polyphenolic compounds. These characteristics, especially internal and external parameters, are similar to a variety. However, each variety has its special characteristics and flavor, which results in different prices and preferences by different people. [3]

Apple produce dealers have warehouses that store different varieties of apple fruits. Therefore, different apple varieties easily get mixed up during harvesting, storage and marketing. Most apple produce dealers will sort the apples manually which results in high cost, subjectivity, tediousness and inconsistency associated with manual sorting. The main objective of this study was to investigate the applicability and performance of Naive Bayes algorithm in the classification of apple fruit varieties. Digital image processing, as a computer-based technique, has been extremely used by scientists to solve problems in agriculture.

II. 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.

A. Color Feature Extraction: As color is most visually striking feature of any image it plays 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 are 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().

B. 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.

skimage.measure.regionprops(label_image, intensity_image=None, cache=True)

C. 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% classification results in [35]. Shape, texture and color (HSV) feature extraction is used to classify 20 categories of fruits in [36]. Color, shape, and texture feature extracted with PCA, biogeography-based optimization (BBO) and feed forward neural network (FNN) to classify 18 categories of fruits in [37] which achieves 89.11% accuracy. Naive Bayes is used for apple fruit classification in [38] with 91% accuracy. For computing shape index, Python function is

skimage.feature.shape_index(image, sigma=1, mode='constant', cval=0).

II. Literature Review

Fernando et al. 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 eigenspace to arrive at a score matrix used to compute defective maps and 94.2% accuracy was reported.[1] Cho et al. used hyperspectral fluorescence imaging for detecting cracking defects on cherry tomatoes[2] while Omid et al. 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. 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. [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 [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. 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. Dubey et al. 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. [39, 40]

III. METHODOLOGY

This part describes the process of analysis and design, which describes the apple classification system structure chart. The details of each element are described below:

A. Materials and Apple Samples: The experimented apple varieties included: golden delicious, honey crisp and pink lady, (Fig 1) which were bought from the local market.

Fig. 1: Apple varieties: (a) Golden delicious (b) Honey crisp (c) Pink lady

In the presented method, color and size features were extracted from the apple images which were used as inputs for classification by being fed into Naïve Bayes algorithm.

B. Apple varieties classification system architecture: It is a preparation process to obtain apple varieties images. The 150 RGB color images of apple varieties were captured using a phone camera with a pixel resolution of 2048x1024 on a white background.

1. Image Acquisition: These images were cropped into smaller images and stored in JPG format. The acquired apple varieties images are shown in Fig. 2.

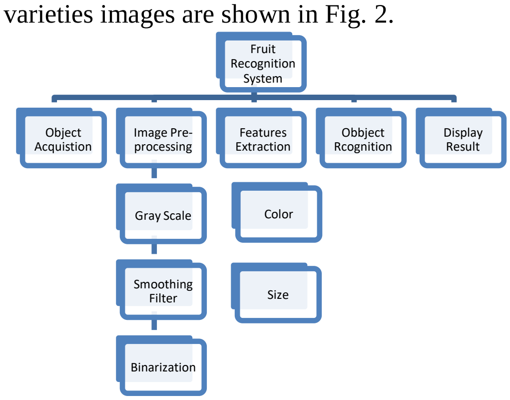

Fig. 2: Structure Chart of Fruit Recognition System

2. Image Segmentation and Pre-processing: The raw data was subjected to several preliminary processing steps to make it functional in the descriptive stages of classification and grading. In order to get apple features accurately, apple fruits images were pre-processed through different pre-processing methods. These methods were converting RGB to grayscale images and filtering the images to remove noise as described below:

a. Converting RGB to Gray Scale Image: The segmentation and pre-processing task are the initial stages before the image is used for the next process. The main objective of this process is to obtain the binary image with converting method.

b. Filtering: The averaging filter was implemented in this process to remove noise. The average filter computes the mean (average) of the gray-scale values within a rectangular filter window surrounding each pixel. This has the effect of smoothing the image (eliminating noise). The filtered pixel was calculated using the equation below:

$$\boldsymbol{r} = \frac{\boldsymbol{a1} + \boldsymbol{a2} + \cdots \ldots \ldots \boldsymbol{a9}}{\boldsymbol{9}}$$

D. Machine Learning Methods: There are various machine learning methods but we have discuss some of them for fruit classification. As the last phase of fruit classification and grading process is knowledge-based comparison and decision making, machine learning algorithms play very important role as classifier and decision makers. In below section, we have briefly described GNB, SVM, Decision Tree and Logistic Regression.

a. Naive Bayes: Naive Bayes classifier is a probabilistic classifier based on the Bayes theorem, considering Naive (Strong) independence assumption. Naive Bayes classifiers assume that the effect of a variable value on a given class is independent of the values of another variable. This assumption is called class conditional independence. Naïve Bayes can often perform more sophisticated classification methods. It is particularly suited when the dimensionality of the inputs is high. When we want more competent output, as compared to other methods output we can use Naïve Bayes implementation. Naive Bayes is used to create models with predictive capabilities.

$$\text{Probability (B given A)} = \frac{\text{Probability A and B}}{\text{Probability}}$$

1. Naive Bayes Training and Testing: In this stage, there was an apple varieties image database consisting of 50 samples of golden delicious apple images, 50 samples of pink lady apple image and 50 samples of honey crisp apple image which were used for training, validation, and testing purposes

b. Logistic Regression Model: The Logistic Regression is a regression analysis where the response variable is binary, which means it can only assume 0 or 1 values. The explanatory variables can be either discrete or continuous. For this model the main components are:

Random Component- The probability distribution f of the response variable is Binomial.

$$Y_i \sim \text{Binomial}\ (n_i;\ \pi_i)$$

Where n_i is the binomial denominator and π_i is the probability

Systematic Component- It is the linear combination of the explanatory variables.

$$n_i = x_i^T\beta$$

Link Function; the link function is the logit function.

$$n_i = \text{logit}(\pi) = \log \frac{\pi}{1-\pi}$$

c. Decision Tree: Decision tree model output is easy to interpret and it provides the rules that drive a decision or event; in the above use case we can get the rules that lead to don't play scenario, that is 1) sunny and temperature >30°c 2) rainy and windy is true. Often businesses might be interested in these decision rules rather than the decision itself. For example, an insurance company might be interested in the rules or conditions in which an insurance applicant should be sent for a medical checkup rather than feeding the applicants data to a black box model to find the decision. Use training data to build a tree generator model, which will determine which variable to split at a node and the value of the split. A decision to stop or split again assigns leaf nodes to a class. An advantage of a decision tree is that there is no need for the exclusive creation of dummy variables.

d. Support Vector Machine (SVM): One of the powerful classification algorithms that have shown state of-the-art performance in different varieties of classification tasks is SVM. Classification of both linear and nonlinear data is done using a new method by SVM. Using kernel functions, SVM nonlinearly maps data to a high-dimensional space

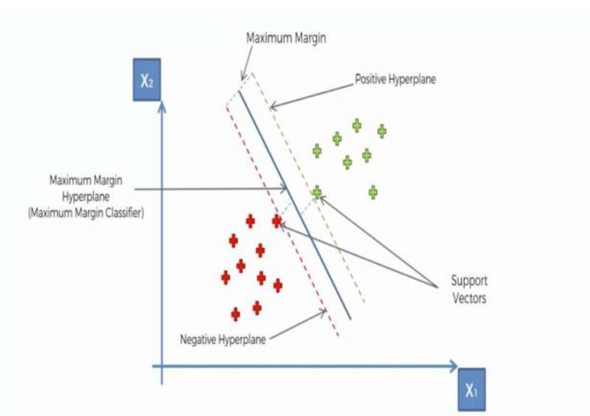

Fig 3: SVM intuition [41]

In that high dimensional space it tries to find the linear optimal hyper plane that separates data with maximum margin. SVM was proposed for only 2-class problems; in multi-class problem SVM is extended using near-against-one or one-against-all strategies.

SVM tries to draw a hyper plane between two classes such that the distance between support vectors can be maximized. SVM support vectors, which are nothing but extreme points of both classes that is the reason why SVM is considered special. Basic concepts of SVM working are shown in below fig. 3.

Sample Python script for making SVM is shown below.

 # Fitting SVM to the Training set

from sklearn.svm import SVC

classifier = SVC(kernel = 'linear', random_state = 0)

classifier.fit(X_train, y_train)

 # Predicting the Test set results

y_pred = classifier.predict(X_test)

Image classification for detection of winter grapevine buds in natural conditions is performed using scale-invariant features transform, bag of features and support vector machines in [41].

IV. Result Discussion

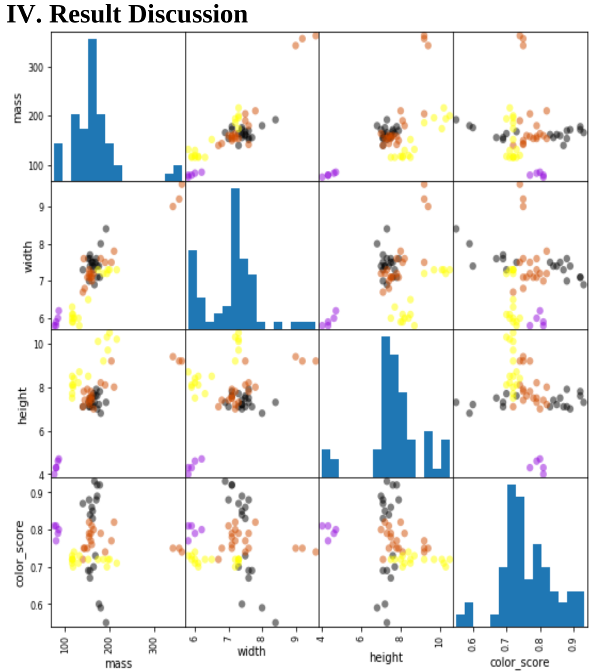

Figure 4: Scatter matrix for each input variables

Comparison of the apple verities accuracy for the training and testing data set showed that the highest accuracy in Decision Tree was observed in apple, lemon, mandarin and orange. The accuracy of the training data was 100%

and on testing data was 73%. This can be attributed to its unique color (green) which was easily distinguishable from the other apple varieties whose colors were almost similar. Similarly we have to work on other input variable for another fruits.

A. Image Classification: After training the system, it then classified the apple varieties whether it is golden delicious apple, granny_smith apple or honey crisp apple during testing and training stages.

B. Evaluation of the System: To evaluate the performance of the system, statistical analysis of experimented results was done. Statistical results in terms of accuracy was calculated

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

S. No.	Classifiers	Accuracy	
		Training set	Test set
1	Logistic Regression	0.7	0.4
2	GNB	0.86	0.67
3	Decision	1	0.73
4	SVM	0.61	0.33

Table 1: Accuracy of training and test set with different classifiers

V. CONCLUSION

Fruit classification system prototype using image processing technique and Gaussian Naive Bayes algorithm, Logistic Regression, Decision Tree and Support Vector Machine was built using python platform environment. The results related to the three apple varieties: granny_smith, braeburn, golden delicious and cripps_pink and other fruit like mandarin, lemon and orange showed that the averaged values of the estimated accuracy for training and testing data set 100% and 73% respectively. Through previous research works, the literature review identified MLP-Neural, fuzzy logic, principal components analysis and neural networks as other technique which have been used previously to classify apple varieties. Comparison of their classification accuracy with that of Decision Tree technique showed that the accuracy of Decision Tree was higher than the accuracy of principal components analysis, fuzzy logic and MLPNeural with 100%, 91%, 90%, 89%, and 83% respectively. The study indicated that Decision Tree has good potential for identifying apple and other fruit varieties nondestructively and accurately. Though this system cannot match the accuracy of the human eye and hand, but the speed and the cost at which they work can be easily be overcome.

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