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Fruit Classification based on Shape, Color and Texture using Image Processing Techniques

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ABSTRACT

Grading and sorting of agricultural products such as fruits and vegetables are very important in post-harvesting process. In manual sorting efficiency totally depends upon the operators, so it is very time-consuming, costly, less efficient process. While exporting to market, quality of fruits must be very good. Grading of fruits is very important because it fetches a high price in a market. Grading and sorting are done based on the fruits size, color, volume, shape and texture. In this review paper, different methods of size, color, volume, and shape and texture detection are discussed. For color detection direct color mapping method, for texture detection Direct curvelet transform and Gabor wavelet transform, for shape detection Discrete wavelet transform, Fourier transform of a body.

Keywords:Shape,Color,Texture,Artifical neural network, Gray level co-occurrence matrix

1. INTRODUCTION

The external features such as color, size, texture, different flaws and shape in the products to be offered to the market are important features in classification and grading. One of the most important quality features in fruits and vegetables is their appearance. The appearance not only affects the market value of the products, its preferences and the choice of the consumer, but it also affects the interior quality to a certain extent. Problems arising from processes such as classification, packaging and storage of fresh fruits and vegetables before they are placed on the market determine the market price formation and consequently affect the producer income (Pezikoğlu et al 2004). Manual quality control of the fruit takes time and labor intensive. Therefore, computerized vision systems are widely used for automation-based external quality control of food and agricultural products. Today, with advances in machine vision can produce accurate, fast, objective and efficient results in the non-destructive fruit classification due to the availability of low-cost hardware and software (Naik and Patel 2017). According to the report of the Fresh Fruit and Vegetable Workshop published by the General Directorate of Agricultural Research and Policies in 2019, there was an increase of 24.03% in total fruit yield, 21.03% in the production area and 50.11% in the production amount. However, this increase causes approximately 30-40% of product to be wasted in total production due to wrong mechanization applications after harvest. Applications of post-harvest technologies can minimize the loss of fresh fruits and vegetables from harvest to consumption, reduce quantitative and qualitative losses, as well as maintain product quality, such as nutritional value, physical appearance and sensory properties. Some studies show that there are large differences between post-harvest losses of developing and developed countries, with estimated losses between 2% and 23% (Singh et al 2014). Studies on image processing have continued from past to present. For example; some of the researchers were used image processing techniques for edge detection, feature extraction and color detection of yellow, red and green apples in their study on yield mapping in peach fruit, usingimage processing techniques such as histogram thresholding and logarithm transformation, color, texture and shape of images taken under natural conditions. Feature extraction method has been used and algorithms have been developed. In the event that a fruit comes in front of the camera, the system processes the image taken from the camera and provides numerical and visual information about the size and color of the fruit examined on the screen (Tonguç 2007; Kim et al 2009; Kurtulmuş et al 2014). The researcher stated that some of the algorithms he developed have been successful in determining the fruit at the level of 85%. Sungur and Özkan (2015) made a quality control application using MATLAB software to detect pollution in chicken eggs and calculate egg volume. The researcher used the fuzzy logic algorithm to determine the degree of quality. According to the results obtained, the algorithm developed works with 98% accuracy. Örnek (2014) investigated the grading efficiency of the real-time image processing system developed with transverse and longitudinal roller-type mechanical carrot sorting machines. The classification of carrots on a belt, which can speed adjusted by a geared motor with classification machine is based on the analysis of these images. According to the results obtained, the ratio of carrots falling to the faulty section in a transverse roll, a longitudinal roll and real time classification machine was found to be between 0.65% - 99.33%, 18.39% - 88.90% and 5.42% - 9.03. Al-Shekaili et al (2016) classified the types of dates grown in various regions of Saudi Arabia according to their hardness. Instead of the traditional expensive and time-consuming methods used to determine the quality of dried fruits, they used artificial neural network and linear discrimination analysis methods by removing histogram and texture features from 1800 images, for example, in the computer vision system they developed. Researchers classified dried fruits into soft, semi-hard and hard. The results were successful for LDA and 84% for ANN and 77% for ANN. Jhawar (2016) classified taken from 160 orange photographs using the pattern recognition method. Designed classification system; data collection and processing, feature extraction and making decisions. Images were taken at a resolution of 640 × 480 pixels with a digital camera from a special box illuminated with 430 luxurious lights. According to the results of the study, 90% and 98% success was achieved in the classification of oranges. Ishikawa et al (2018), in their study, classified the strawberries by using the shape information taken from digital images. Using the SHAPE software, they used fruit length, width, projection area and fruit border lines data from 2969 photos for classification. They emphasized that the method of machine learning was successful in identifying strawberry fruits of nine different shapes. Li et al (2019) have developed an online optical and spectroscopic-based system for the rapid determination of internal and external quality in apples after harvest. A new image segmentation method has been developed in order to determine the image of apple containing all surface information in the online detection system consisting of the external quality detection mechanism and the internal quality detection mechanism. In the study, the fruit external quality assessment rate was 96.76%, the correlation coefficient in size measurementwas 0.9763, and the root-mean-square error (RMS error) was 1.3243 mm. In this work, apple, quince and orange fruit varieties were tried to be classified according to the color and size by developing an image processing algorithm.

2. LITERATURE REVIEW

Identification of fruits and vegetables are implemented in different areas. The most common areas are identification in the retail business and in areas where the purpose is to ease the harvest in the perspective of agriculture. Mostly, the identification is done manually by a cashier or via the self-service systems in a store. In this section, different methods of identifying fruits and vegetables will be presented.A company which has made great progress in its technical evolution when it comes to artificial intelligence, image recognition and automating physical work is Amazon. Amazon developed a product, called Amazon Go2, which enabled a shopping experience without cashiers or self-service checkouts. The company built the store where the customers check in with a smart phone using the application Amazon Pay3 . The store is set up with a large number of cameras and sensors. Thanks to computer vision and deep learning algorithms, Amazon managed to create a store where technology identifies the products the customers choose. No checkout is required, the chosen products are debited from Amazon Pay account that the costumer checked in with.StrongPoint is a company, with its headquarters in Norway, offering technical solutions to the retail business. Strong Point recently released an identification system called Digi5 . Digi consists of a user interface displayed on a touch screen, a scale, a camera and a label printer. The software is implemented with image recognition in the identification process and can be compared to the existing counterpart of this project. Digi is new to the market; hence it is not used in many stores. It is an economic issue of the retail business whether the business will change the existing systems or not.Related work including image recognition has been done in the purpose of controlling the vegetation and harvest of fruitage and other growths at fields of farmers. The technology has been used to automate the yield with the help of robotic harvesting However, the issue of creating a fast and reliable fruit detection system persists. This is due to large variation in the appearance of the fruits in field, including color, shape, size and texture properties.

3.PROPOSED METHODOLOGY

In this proposed work, we have applied image processing techniques for detection of plant leaf diseases. The proposed methodology that applied in this work is shown in Figure 1, in which we followed the image acquisition, preprocessing, segmentation, feature extraction using HSV and DWT method and then sample images was tested by SVM classifier.

Data Acquisition: In this step of the methodology, data is needed to be acquired from the project resources. If required, the acquisition is followed by the loading of data for understanding purposes. The data is examined for any patterns, quality problems, and verification. The existing method of fruit classification and crop suggestion require manual involvement, human errors, and the results are uncertain. The method is also time consuming and invasive in nature. But our proposed system overcomes all these errors because it takes into account the physical properties of fruit for classification and prediction.

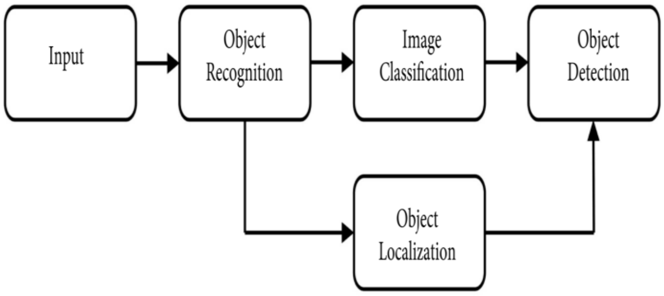


Figure 1: Proposed system for fruit detection

The camera is placed on top of the system and tilted forward towards a flat surface in front of the system. The purpose of this is to minimize the interference from other objects in the surroundings that otherwise could impact the results The input image is matched with a similar image in the dataset that is image retrieval is being done here. For performing this task we need images of fruit, we can either capture these from various regions and stored into a database or we can get these from online sources. Criteria are images used should be colored After gathering images we need to store it on the database

Filtration:

Filtration in our proposed system is done using Gabor filter. Gabor filter is used to pass signals with frequency lower than the cut-off frequency and attenuates all other signals with frequencies greater than the cut-off frequency. In our proposed system Gabor filter is used to remove unwanted components and features from the signals so as to reduce noise in the signal. Gabor filter is also used for shade correction, even brightening and for removing artifacts.

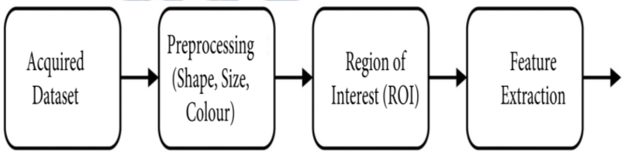


Figure 2: Preprocessing and segmentation steps for fruit detection and classification.

Feature Extraction: Features are the fundamental components of an object. It is used to distinguish one object from the other. Features are also referred to as descriptors. The process of obtaining features from an object is known as description of an object. In our proposed system feature extraction is done by two methods

1. Colour based feature extraction

2. Texture based feature extraction

Colour Based Feature Extraction:

Colour moments display a gray-scale representation of each colour channel. Notice that each separated colour plane in the figure contains an area of white. The white corresponds to the highest values (purest shades) of each separate colour. For example, in the red channel image, the white represents the highest concentration of pure red values. As red becomes mixed with green or blue, gray pixels appear. The black region in the image shows pixel values that contain no red values, in other words, when R == 0. Display a colour representation of each colour channel. In these images, the desired colour channel maintains its original intensity values and pixel values in the other two-colour channels are set to create an all-black channel.

Colour correlation

Matching is an important task in computer vision because the accuracy of the 3D reconstruction depends on the accuracy of the matching. A lot of matching algorithms have been used the present paper focuses on matching using correlation measures whose main hypothesis is based on the similarity of the neighbourhoods of the corresponding pixels. Hence, in this context, we consider that a correlation measure evaluates the similarity between two-pixel sets. In our previous work, the commonly used correlation measures are classified into five families and, as we are particularly concerned with the occlusion problems, new correlation measures.

to compute the correlation with each color component and then to merge the results; to process a principal component analysis and then to compute the correlation with the first principal component; to compute the correlation directly with colors. Moreover, an evaluation protocol which enables to study the behaviour of each method with each color space is required to highlight the best way to adapt correlation measures to color and the improvement of the efficiency of correlation-based matching

HSV Based Histogram

Hue Saturation Value (HSV), Gray Level Co-occurrence Matrix (GLCM) are used for Colour based feature extraction in our proposed system. Grey-Level Co-occurrence Matrix texture measurements have been the workhorse of image texture since they were proposed. To many image analysts, they are a button you push in the software that yields a band whose use improves classification - or not. The original works are necessarily condensed and mathematical, making the process difficult to understand for the student or front-line image analyst. This document concerns some of the most commonly used texture measures, those derived from the Grey Level Co-occurrence Matrix (GLCM). The essence is understanding the calculations and how to do them. This involves

- Defining a Grey Level Co-occurrence Matrix (GLCM)
- Creating a GLCM
- Using it to calculate texture in the exercises.
- Understanding how calculations are used to build up a texture image
- Viewing examples of the texture images created with various input parameters

Third and higher order textures (considering the relationships among three or more pixels) are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty. There has been some recent development of a more efficient way to calculate third-order textures. The third group of GLCM texture measures consists of statistics derived from the GLC matrix.

Texture based feature extraction

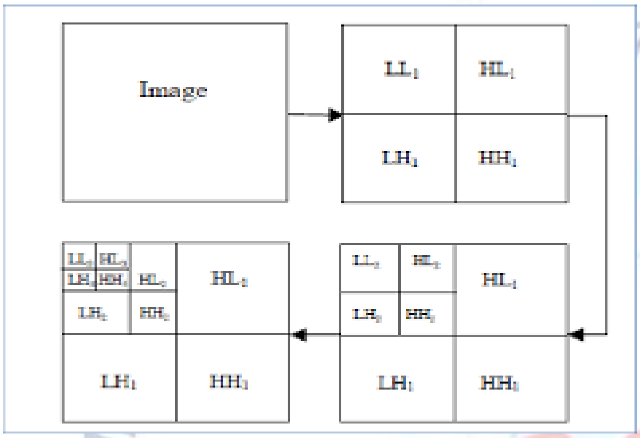
Discrete wavelet transform:

The Discrete wavelet transform and theory of multi resolution analysis can be found in a number of articles and books that are available on this topic, and it is beyond the scope of this tutorial.

The DWT of image f(x, y) can be defined as:

$$f(x,y) = A_n^q f(x,y) + \sum_{s=1}^{n} [D_{s,1}^q f(x,y) + D_{s,2}^q f(x,y) + D_{s,3}^q f(x,y)]$$

Where A and D coefficients and are approximation and difference directional components respectively, which also be called as the low frequency sub bands and high frequency sub bands of image.



The analytic extension is constructed by real wavelet and its 2-D After image is decomposed by DWT, we can obtain a low frequency part and n groups of high frequency parts. The DWT decomposition structure of image is shown in Fig. 1. “Low” represents the low frequency part which composed by four low frequency sub bands, that is, band 1 to band 4. At each level, the high frequency information is presented in 3 directions (horizontal (H), vertical (V) and diagonal (D)), and there are four sub bands (band 1, band 2, band 3, band 4) in each direction. These four sub bands can be transformed into one magnitude and three phases.Having said that, we now look how the DWT is actually computed: The DWT analyzes the image at different frequency bands with different resolutions by decomposing the image into a coarse approximation and detail information. DWT employs two sets of functions, called scaling functions and wavelet functions, which are associated with low pass and high pass filters, respectively.

$$y_{high}[k] = \sum_{n} x[n] \cdot g[2k - n]$$
$$y_{low}[k] = \sum_{n} x[n] \cdot h[2k - n]$$

where $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the and low pass filters, respectively, after sub sampling by 2. This decomposition halves the time resolution since only half the number of samples now characterizes the entire image. However, this operation doubles the frequency resolution, since the frequency band of the image now spans only half the previous frequency band, effectively reducing the uncertainty in the frequency by half. The above procedure, which is also known as the sub band coding, can be repeated for further decomposition.

Feature Extraction

Feature extraction is the techniques or method that used to measure of difference characteristics of image segments also its process to represent raw image in its reduced form to facilitate decision making such as pattern classification. Each segmented region in a scene may be described by a set of such features In this work used texture analysis method; The Spatial Gray Level Dependency matrix (SGLD) matrix generator, which decomposes the input image into texture features.

The texture features are: Energy(EG), Correlation(CO), Inertia(IN), Entropy(EN), Inverse Difference Moment(IDM), Sum Average(SA), Sum Variance(SV), Sum Entropy(SE), Difference Average(DA), Difference Variance(DV), Difference Entropy(DE).

Data Set

The data set is divided into 10 different classes. Each class represents one type of fruit and vegetable. The chosen classes are apple, avocado, banana, pear . These classes are chosen because some fruits and vegetables have similar appearances and are frequently bought in retail markets. Limitations to the data set have been done in order to not make the project to extensive. These limitations are that all types of a fruit or vegetables reside under the same class. This means all types of apples reside under the apple class and similar for each fruit. Images for the data set are collected from . Each class consists of approximately 80 images. This sub set of images create a base data set to train the networks.

Classification: Classification is the process of categorization, we apply some classification algorithm to classify different types of fruit .SVM can be used.

If we drew a perpendicular line from each point to the regression line, and took the intersection of those lines as the approximation of the original data point, we would have a reduced representation of the original data that captures as much of the original variation as possible. Notice that there is a second regression line, perpendicular to the first, shown in Figure 3.

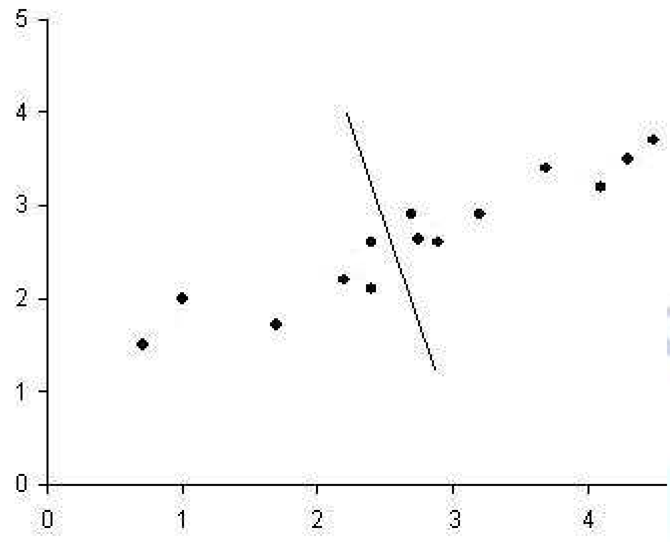


Figure 3: Regression line along second dimension captures less variation in original data.

This line captures as much of the variation as possible along the second dimension of the original data set. It does a poorer job of approximating the original data because it corresponds to a dimension exhibiting less variation to begin with. It is possible to use these regression lines to generate a set of uncorrelated data points that will show sub groupings in the original data not necessarily visible at first glance.These are the basic ideas behind SVM: taking a high dimensional, highly variable set of data points and reducing it to a lower dimensional space that exposes the substructure of the original data more clearly and orders it from most variation to the least. What makes SVM practical for is that you can simply ignore variation below a particular threshold to massively reduce your data but be assured that the main relationships of interest have been preserved

4. RESULTS& DISCUSSION

In this section, we depict the dataset of fruits classifications and discuss about the execution and the proficiency of the framework. In the following segment we describe the dataset used in this experiment, in section the performance of the proposed combined features are given and compared with colour, texture and shape features proposed We have used 80 images of normal apple, guava, pear, banana fruits. Each class has 10 images. This dataset is also used in the analysis.

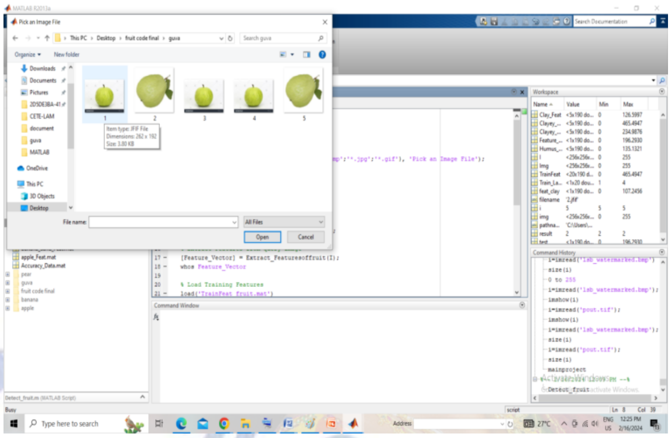


Figure 4: Browsing the input data

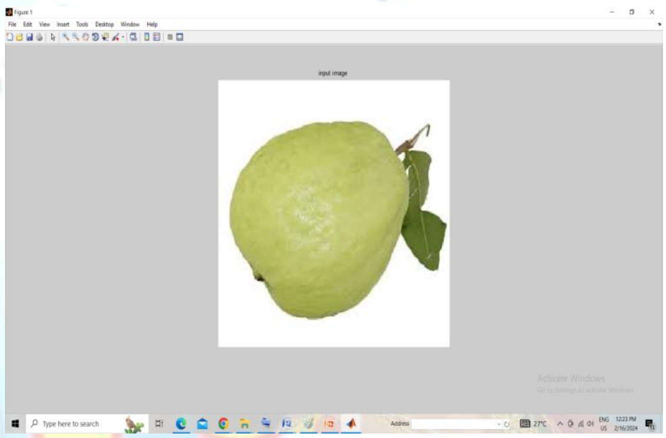


Figure 5: Input Image capturing from camera sensor with 8 mega pixel

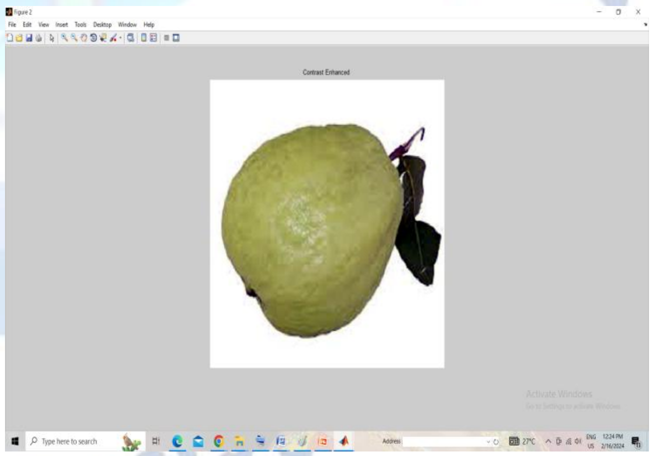


Figure 6: To enhance for input image by using white level balance process

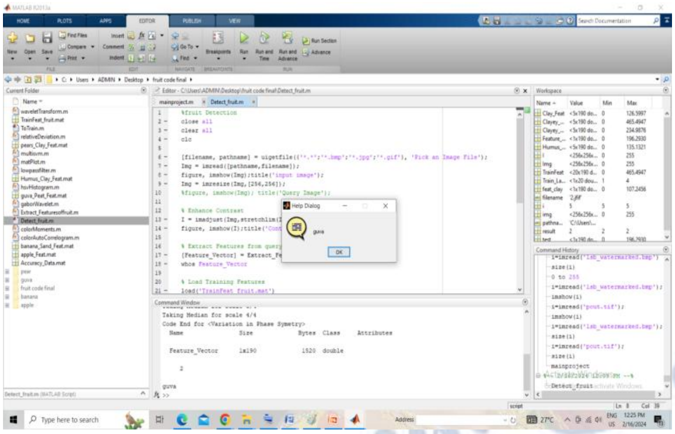


Figure 7: Fruit name is classified from database features by used supervised SVM classifier

This project exposes a different methodology wherein the given RGB when converted to Hue gives 100% accuracy rate if SVM is used. Apart from the existing methods of extracting colour features, this methodology uses texture features andstatistical feature for all the coefficients obtained from wavelet transformation using Haar filter at both level one and level two.This is the main drawback of shape basis classification. To overcome this drawback a new feature is used that is color. Figure 8 shows the classification percentage on color basis. As the classification accuracy is improved to 94% for guava But the classification accuracy is efficiently improved when color and texture feature are amalgamated (Figure 9). Classification accuracy is improved for all fruits and 97.2 % pomegranates are accurately classified.

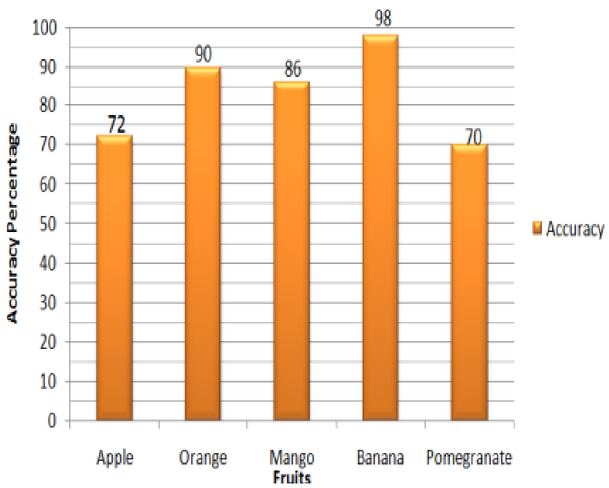


Figure 9: Shape Based Classification

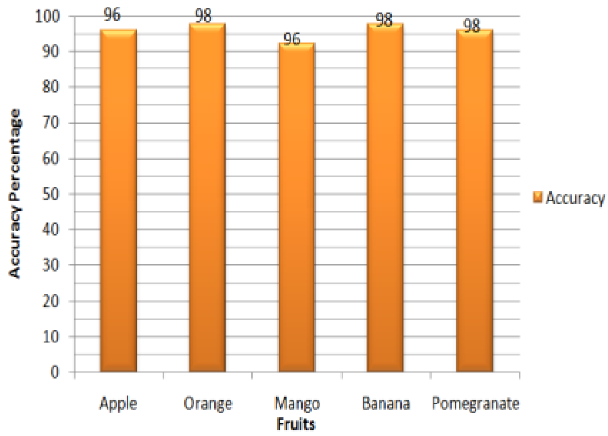


Figure 10:Color+Texture Based Classification

Only the Hue component image was considered for experimentation from the HSI image as it alone gave 100% classification accuracy Colour features were not used to classify the image that was one among the unique feature of this proposed system

4.CONCLUSIONS

In this work, a co-occurrence pattern for fruit quality and sub-category detection based on features, color, shape size and texture features are presented. The estimated size of the fruits matches with the actual size of the dataset verified by the distribution of RGB color space is observed using the color histogram, and then the color moment is computed to find color uniformity. The shape of the fruit image is identified as round or oval. The size of the fruit is evaluated based on the major axis and minor axis. The texture features are computed using a transform-based hybrid DWT The main aim of this study is to investigate the performance SVM methods is better on both datasets.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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