Application of Image Processing in Fruit and Vegetable Analysis: A Review

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2 authors:

Shiv Ram Dubey
IIIT Sri City, India

Anand Singh Jalal
GLA University

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Shiv Ram Dubey, Anand Singh Jalal
GLA University Mathura, India

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ABSTRACT

Images are the important source of data and information in the agricultural sciences. The use of image processing techniques is of outstanding implication for the analysis of agricultural operations. Fruit and vegetable classification is one of the major applications that can be utilized in the supermarket to automatically detect the kind of the fruit or vegetable purchased by the customer and to generate the costs for it. Training on-site is the underlying prerequisite for this type of arrangement, which is generally caused by the users having little or no expert knowledge. In this manuscript, we explored various methods which addressed fruit and vegetable classification as well as fruit disease recognition problem. We surveyed the approaches used for fruit disease detection, segmentation and classification of images using image processing. We also compared state-of-the-art methods in this manuscript in two scenarios i.e. fruit and vegetable classification and fruit disease classification. The methods surveyed in this paper are able to distinguish between different kind of fruits and its diseases which are very alike in color and texture.

KEYWORDS: Image Processing, Fruit Analysis, Fruit Disease Detection, Color, Shape, Texture

1. 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 the 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. The computer based image processing is undergoing rapid evolution with ever changing computing systems. The dedicated imaging systems available in the market, where the user can press a few keys and get the results, are not very versatile and more important, they have a high price tag on them. Additionally, it is hard to understand as to how the results are being produced. We have attempted to investigate the solutions through published literature which presents classification problems in a most realistic way possible.

Recognition system is a 'grand challenge' for the computer vision to achieve near human levels of recognition. The fruits and vegetable classification is useful in the supermarkets where prices for fruits purchased by a client can be defined automatically. Fruits and vegetable classification can also be utilized in computer vision for the automatic sorting of fruits from a set, consisting of different kind of fruits. Picking out different kind of vegetables and fruits is a recurrent task in the supermarkets, where the cashier must be capable to identify not only the species of a particular fruit or vegetable (i.e., banana, apple, pear) but also identify its variety (i.e., Golden Delicious, Jonagold, Fuji), for the determination of its cost. This problem has been solved for packaged products, but most of the time consumers want to pick their product, which cannot be packaged, then it must be weighted. Assignment of codes for each kind of fruit and vegetable is a common solution to this problem; but this approach has some problems such as the memorization, which may be a reason for errors in pricing. As an aid to the cashier, a small book with pictures and codes is issued in many supermarkets; the problem with this approach is that flipping over the booklet is time-consuming.

This research reviews several image features and image descriptors in the literature and presents a system to solve the problem by adapting a camera at the supermarket that recognizes fruits and vegetables on the basis of color and texture cues. Formally, the system must output a list of possible types of species and variety for an image of fruit or vegetable. The input image contains fruit or vegetable of single variety, at random position and in any number. Objects inside a plastic bag can add hue shifts and specular reflections. Given the variety and the impossibility of predicting which types of fruits and vegetables are sold, training should be done on site by someone having little or no technical knowledge. The solution of the problem is that the system must be able to achieve a higher level of accuracy by using only a few training examples. Monitoring of health and detection of diseases is critical in fruits and trees for sustainable agriculture. To the best of our knowledge, no sensor is available commercially for the real time assessment of trees health conditions. Scouting is the most widely used method for monitoring stress in trees, but it is expensive, time consuming and labor-intensive process. Polymerase chain reaction which is a molecular technique used for the identification of fruit diseases, but it requires detailed sampling and processing procedure.

Early detection of disease and crop health can facilitate the control of fruit diseases through proper management approaches such as vector control through fungicide applications, disease-specific chemical applications and pesticide applications; and improved productivity. The classical approach for detection and identification of fruit diseases is based on the naked eye observation by experts. In some of the developing countries, consultation with experts is a time consuming and costly affair due to the distant locations of their availability. Automatic detection of fruit diseases is of great significance to automatically find the symptoms of diseases as early as they appear along the growing fruits. Fruit diseases can cause significant losses in yield and quality appeared in harvesting. For example, soybean rust (a fungal disease in soybeans) has caused a significant economic loss and just by removing 20% of the infection, the farmers may benefit with an approximately 11 million-dollar profit (Roberts et al., 2006). An early detection system of fruit diseases can aid in decreasing such losses caused by fruit diseases and can halt further spread of diseases.

The various types of diseases of fruits determine the quality, quantity, and stability of yield. The diseases in fruits not only reduce the yield but also deteriorate the variety and its withdrawal from the cultivation. Fruit diseases appear as spots on the fruits and if not treated on time, cause the severe loss. Excessive use of a pesticide for fruit disease treatment increases the danger of toxic residue level of agricultural products and has been identified as a major contributor to the ground water contamination. Pesticides are also among the highest components in the production cost and also it is not well as the health perspective so, their use must be minimized. Therefore, this paper reviewed such approaches which can detect the diseases in the fruits as soon as they produce their symptoms on the fruits such that proper management treatment can be applied.

A lot of work has been done to automate the visual inspection of the fruits by machine vision with respect to size and color. However, detection of defects in the fruits using images is still problematic due to the natural variability of skin color in different types of fruits, high variance of defect types, and presence of stem/calyx. To know what control factors to consider next year to overcome similar losses, it is of great meaning to examine what is being celebrated. Some fruit diseases also infect other areas of the tree, causing diseases of twigs, leaves and branches. The precise segmentation is required for the defect detection. The early detection of fruit diseases (before the onset of disease symptoms) could be a valuable source of information for executing proper pest management strategies and disease control measures to prevent the development as well as the spread of fruit diseases.

The aim of this review paper is to research the use of image processing and computer vision techniques in the food and farming industry. The main objective is to review the approaches to recognize species and a diversity of fruits and vegetables and type of diseases present in the fruit from their pictures.

2. LITERATURE REVIEW

This section reviewed the study done by several researchers in the area of image categorization, fruits recognition, fruit and vegetable classification, fruit disease identification using images. Fruit and vegetable classification and fruit disease identification can be seen as an instance of image categorization. Most of the researches in the field of fruit recognition or fruit disease detection have considered color and texture properties for the categorization. Most of the work for fruit recognition is done with the fruits located on trees, but we restrict ourself to the classification of fruits and vegetables amongst the several kinds of fruits and vegetables. Most of the work for the fruit disease detection done in the literature is restricted to the detection of a single type of disease only. In this section, several approaches used by researchers is discussed with the aim of being aware of the latest research carried out, which are related to the formulated problems in this paper.

2.1 Issues and Challenges

We will survey fruits and vegetables recognition and fruit disease identification methods in this manuscript with respect to the number of challenges addressed. Here, we list some issues and challenges which may be the basis to evaluate the different methods. The input images may contain fruit or vegetable of more than one variety in arbitrary position and in any number. Many kinds of fruits and vegetables are subject to significant variation in shape, texture and color, depending upon their ripeness. For example, Orange ranges from being green, to yellow, to patchy and brown. Using just one image feature to secure the class separability might not be sufficient, so it is necessary to extract and combine those features which are useful for the fruit and vegetable recognition problem. Sometimes, the object may be inside the plastic bag that can add hue shifts and specular reflections. Different classifier may produce different results, so the selection of classifier must also be addressed. In the literature, available classifiers works on two classes only, but in the produce classification problem we consider more than two classes, so it is a major issue to use a binary classifier in a multiclass scenario. Background subtraction may become necessary to reduce the scene complexities such as illumination variation, sensor capturing artifacts, background clutter, shading, and shadows. The result of the system heavily depends upon the efficient working of the image segmentation method, so efficient image segmentation must be used. The performance of the fruit disease recognition system also depends upon the defect segmentation, so precise defect segmentation is required. It might be interesting to consider the number of training examples because more number of training examples require more time to train the system. The system must perform better in situations where the system is trained with less training examples.

2.2 Fruit and Vegetable Recognition and Classification

Recently, a lot of activity in the area of image categorization has been done. With respect to the produce fruit and vegetable classification problem, Veggie-Vision (Bolle et al., 1996) was the initial attempt of a supermarket produce recognition system. They used color, texture and density (thus taking more information) features. Density is calculated by dividing weight with the area of the fruit. The reported accuracy was ≈ 95% when color and texture features are combined, but top four responses are used to achieve such result. Rocha et al. (2010) presented a unified approach that can combine many features and classifiers. The authors approached the multi-class classification problem as a set of binary classification problem in such a way that one can assemble together diverse features and classifier approaches custom-tailored to parts of the problem. They have achieved classification accuracy up to 99% for some fruits, but they fused three features, namely Border-interior classification (BIC), Color coherence vector (CCV), and Unser features and used top two responses to achieve them. Their method shows poor results for some type of fruit and vegetable such as Fuji Apple. Arivazhagan et al. (2010) combined the color and texture features to classify the fruits and vegetables. They used minimum distance classifier and achieved 86% accuracy over the dataset having 15 different types of fruits and vegetables. Further, Faria et al. (2012) presented a framework for classifier fusion for the automatic recognition of fruits and vegetables in a supermarket environment. They combined low-cost classifiers trained for specific classes of interest to enhance the recognition rate. Chowdhury et al. (2013) have recognized 10 different vegetables using color histogram and statistical texture features. They have gained the classification accuracy upto 96.55% using 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 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.

In (Dubey, & Jalal, 2012a; Dubey, & Jalal, 2013; Dubey, 2013), a framework for fruits and vegetables recognition and classification is proposed. They have considered images of 15 different types of fruit and vegetable collected from a supermarket. Their approach first segment the image in order to extract the region of interest and then calculate image features from that segmented region, which is further used in training and classification by a multi-class support vector machine. They have 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. 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. They achieved accuracy up to 96.36% on 110 tomato images.

Fruit detection greatly affects the robot’s harvesting efficiency because it is an unstructured environment with changing lighting conditions. Bulanon et al. (2009b) enhanced the fruit portion by a red chromaticity coefficient and used a circle detection method for classification of the individual fruits. To improve fruit visibility, they acquired multiple views from different viewing angles for a portion of a tree canopy. According to their results, fruit visibility improved from 50% to about 90% by acquiring multiple views. Date fruits are popular in the Middle East and have a growing international presence. Sorting of dates can be a tedious job and a key process in the date industry. Haidar et al. (2012) presented a method for classification of date fruits automatically based on pattern recognition and computer vision. They extracted appropriately crafted mixture of 15 different visual features, and then, tried multiple classification methods. Their performance ranged between 89% and 99%. Jimenez et al. (1999) presented a methodology that is able to identify spherical fruits in natural environment facing difficult situations: occlusions, shadows, bright areas and overlapping fruits. Range/attenuation data are sensed by a laser range-finder sensor. The 3-d position of the fruit with radius and reflectance are obtained after the recognition steps.

Vegetable quality is oftentimes referred to color, shape, mass, firmness, size and bruises from which fruits can be classified. Lino et al. (2008) classified the lemons and tomatoes by the size and color of the fruit. Peach fruits are recognized in (Liu et al., 2011) in a natural scene. The red peach region is obtained first and then a matching expansion is used to recognize the entire region. The potential center point of the fitting circle is calculated by the intersection of the perpendicular bisector of the line on the contour. Finally, the center point and radius of the fitting peach circle are obtained by calculating the statistical parameters of the potential center points. Variations in antioxidant profiles between fruits and vegetables are studied in (Patrasa et al., 2011) using pattern recognition tools; classification was done based on global antioxidant activity, levels of antioxidant groups (ascorbic acid, total anthocyanins, total phenolics) and quality parameters (moisture, instrumental color). Interrelationships between the parameters considered and the different fruits and vegetables were discovered by hierarchical cluster analysis (HCA) and principal component analysis (PCA). Patel et al. (2011) presented the fruit detection using improved multiple features based algorithm. They designed an algorithm with the aim of calculating different weights for different features like color, intensity, edge and orientation of the input image. The approximate locations of the fruit within an image are represented by the weights of the different features. They achieved the detection efficiency up to 90% for different fruit image on a tree, taken from different positions.

Thermal imaging is an approach to convert the pattern of invisible radiation of an object into visible images to facilitate the feature extraction and analysis. If temperature differences can be used to assist in analysis, diagnosis, or evaluation of a product or process, then Infrared thermal imaging technology can be successfully applied. The potential scope of thermal imaging in food and agriculture industry includes disease and pathogen detection in plants, predicting water stress in crops, predicting fruit yield, planning irrigation scheduling, bruise detection in fruits and vegetables, evaluating the maturing of fruits, temperature distribution during cooking, and detection of foreign bodies in food material. Vadivambal, & Jayas (2011) reviewed the application of thermal imaging in food and agriculture industry and highlighted on the potential of thermal imaging techniques in various agricultural process. The major advantage of infrared thermal imaging approach is the non-contact, non-destructive, and non-invasive nature of the technique to find the temperature distribution in a short period of time. Seng, & Mirisaee (2009) combined three feature analysis methods: color-based, size-based and shape-based in order to increase the accuracy of recognition. They used nearest neighbor classifier for the classification. They achieved up to 90% accuracy.

Researchers have begun to consider how mobile devices can be used to slow down the burden of recording nutritional intake. Rahman et al. (2012) introduced a concept to integrate camera in a mobile phone for capturing the images of food consumed. These images can be processed automatically to identify the food items present in the image. They generated texture features from food images and demonstrated that this feature leads to greater accuracy for a mobile phone based dietary assessment system.

2.3 Fruit Disease Recognition and Classification

Automatic detection of fruit diseases is essential to automatically detect the symptoms of diseases as early as they appear on the growing fruits. Fruit diseases can cause major losses in yield and quality appeared in harvesting. To know what control factors to take next year to avoid losses, it is crucial to recognize what is being observed. Some disease also infects other areas of the tree, causing diseases of twigs, leaves, and branches. Some common diseases of apple fruits are apple scab, apple rot, and apple blotch (Hartman, 2010). Apple scabs are gray or brown corky spots. Apple rot infections produce slightly sunken, circular brown or black spots that may be covered by a red halo. Apple blotch is a fungal disease and appears on the surface of the fruit as dark, irregular or lobed edges.

With increased expectations for food products of high quality, the need for fast, accurate and objective quality determination in food products continues to grow. To accomplish these requirements, computer vision provides one alternative for a cost-effective, non-destructive and automated technique. This image analysis and processing based inspection approach has found a variety of different applications in the food and agriculture industry. Brosnan, & Sun (2002); Brosnan, & Sun (2004) reviewed the progress of computer vision and emphasizes the important aspects of the image processing technique coupled with recent developments throughout the agricultural and food industry. In (Bennedsen, & Peterson, 2005), a machine vision system is developed for sorting apples for surface defects, including bruises. Defects were detected using a combination of a routine based on artificial neural networks and principal components and three different threshold segmentation routines. They evaluated their routine using 8 apple varieties. The routines ability to find individual defects ranged from 77 to 91% for the number of defects detected and measured area ranged from 78 to 92.7% of the total defective area. Bennedsen et al. (2005) used rotating apples in front of the camera to capture multiple images and removed the dark areas on the apple surface efficiently. Pydipati et al. (2006) have identified the 4 types of citrus diseases including normal one using color co-occurrence methods and generalized squared distance in HSV color space and achieved more than 95% accuracy. Kim et al. (2009) have presented an approach to classify the grapefruit peel diseases. Their dataset consists of the 6 types of diseases including normal one. ROI of the fruit is generated by cropping over which intensity texture features are generated and classified using discriminative analysis. They have gained 96% accuracy.

Bulanon et al. (2008) studied the variation of thermal temporal in the citrus canopy as a potential approach for orange fruit detection. They used a thermal infrared camera and monitored tree canopy on 24 h cycles. Using a portable Dew Point Meter, they measured surface temperature, ambient temperature and relative humidity. Canopy and fruit temperature profile demonstrated large temperature gradient from afternoon (16:00) until midnight. They segmented the fruits very efficiently using image processing techniques in the thermal images during the time range of the largest temperature difference. In (Bulanon et al. 2009a), they fused a thermal image with a visible image of an orange canopy scene to improve fruit detection. A thermal infrared camera captured the thermal image and a digital color camera acquired the visible image. They applied two image fusion approaches, fuzzy logic and Laplacian pyramid transform. Based on their results, the fuzzy logic approach is better than the LPT and both fusion approaches improved detection as compared to thermal image alone.

A hyperspectral imaging system was developed by Qin et al. (2009) for acquiring reflectance images in the spectral region from 450 to 930 nm from citrus samples. They performed spectral information divergence (SID) classification method on hyperspectral images of the grapefruits for differentiating canker from normal fruits and other citrus surface conditions based on quantifying the spectral similarities using a predetermined canker reference spectrum. They reported 96.2% overall classification accuracy using an optimized SID threshold value of 0.008. Crowe, & Delwiche (1996a) proposed the use of three cameras which sense the reflectance in the visible region and narrow bands in the near infrared region for simultaneous color evaluation and fruit defect detection. The visible region information is used in color grading. A narrow band centered at 780 nm is used for concavity identification with structured illumination while a second band centered at 750 nm allowed the detection of dark spots under complex illumination. In another work, Crowe, & Delwiche (1996b) combined two near infrared (NIR) images of each fruit with a pipeline image processing system in real-time. Structured illumination portion information facilitates to distinguish defects from concavities. They estimated the total projected area of defects on each fruit and accordingly classified the defects based on the defect pixel total.

Near-infrared hyperspectral imaging (NIR-HSI) is an emerging technique that combines imaging techniques with the classical NIR spectroscopy in order to obtain spatial and spectral information simultaneously from a field or a sample. The technique is fast, nonpolluting, non destructive, and relatively inexpensive per analysis. Very recently, Dale et al. (2013) presented a review on the NIR-HSI in agriculture and in the quality control of agro-food products. Growing interest in HSI has emerged for quality and safety assessments of agro-food products. Lorente et al. (2012) highlighted the recent works in the field of inspection of fruit and vegetables that use hyperspectral imaging. They explained the different approaches to acquire the images and their use in the inspection of the internal and external features.

Fernando et al. (2010) used an unsupervised method based on a Multivariate Image Analysis strategy which uses Principal Component Analysis (PCA) to generate a reference eigenspace from a matrix obtained by unfolding spatial and color data from defect-free peel samples. In addition, a multiresolution concept is introduced to speed up the process. They tested about 120 samples of mandarins and oranges from four different cultivars: Marisol, Fortune, Clemenules, and Valencia. They reported 91.5% success ratio for individual defect detection, while 94.2% classification ratio for damaged/sound samples. Dubey, & Jalal (2012b) and Dubey, & Jalal (2012c) proposed a method to detect and classify the fruit diseases using image processing techniques. First of all, they detected the defected region by k-means clustering based image segmentation technique, then extracted the features from that segmented defected region which is used by a multi-class support vector machine for training and classification purpose.

Gabriel et al. (2013) proposed a pattern recognition method to automatically detect stem and calyx ends and damaged blueberries. First, color and geometrical features were extracted. Second, five algorithms were tested to select the best features. The best classifiers were Support Vector Machine and Linear Discriminant Analysis. Using these classifiers, they distinguished the blueberries' orientation in 96.8% of the cases. The average performance for mechanically damaged, shriveled, and fungally decayed blueberries were reported as 86%, 93.3%, and 97% respectively. Apple fecal contamination is an important food safety issue. Kim et al. (2002a) detected fecal contaminated apples, by using a hyper spectral reflectance imaging technique in conjunction with the use of PCA. They identified three visible (VIS) to the near–infrared (NIR) and, alternatively, two NIR wavelengths for detection of apples fecal contamination that could potentially be implemented in multispectral imaging systems. In (Kim et al., 2002b), they also investigated that multispectral fluorescence approaches can be incorporated to detect the fecal contamination effect on apple surfaces. In (Pujari et al., 2013a; Pujari et al., 2013b), the diseased fruits are identified for grading of the normal fruits using BPNN classifier with color and texture based features in RGB and YCbCr color spaces and gained nearly 88% of success rate. Recently, they also used ANN/Knowledge base classifier to classify the powdery mildew over 6 types of fruits by combining the color and texture features in RGB color space (Pujari et al., 2014). Kanakaraddi et al. (2014) have computed the disease severity level of pathogenic disease in chilli fruit using only color based features and decision tree.

Kleynen et al. (2005) developed a multi-spectral vision system in the visible/NIR range having four wavelength bands. They classified the defects into four categories: slight, more serious, leading to the rejection and recent bruises. A correlation pattern matching algorithm is used to detect stem-ends/calyxes. Bayes theorem based pixel classification approach and non-parametric models of the defective and non-defective fruits are used for defect segmentation. They achieved good classification rates for apples having serious defects and recent bruises. Based on color information, an approach is proposed to detect 'Golden Delicious' apples defects (Leemans et al., 1998). In the first step, based on the variability of the normal color a model is generated. Each pixel of an apple fruit image is compared with the model to segment the defects. Any pixel is considered as healthy tissue, if it matches with the model. Based on a Bayesian classification approach, a segmentation process is proposed in (Leemans et al., 1999), which used information enclosed in a color image of a bi-color apple. The results showed that most defects, namely bruises, bitter pit, fungi attack, scar tissue, frost damages, scab and insect attack, are segmented.

An automated bruise detection system can help the fruit industry to reduce potential economic losses and to provide better fruit for the consumer. Lu (2003) investigated the potential of near–infrared (NIR) hyperspectral imaging in the spectral region between 900 nm and 1700 nm for detecting bruises on apples. They detected both new and old bruises on apples using NIR hyperspectral imaging system.

Based on a low pass Butterworth filter with a cutoff frequency $D0 = 7$ (i.e. the filter response will be maximally flat for $D0 < 7$), a lighting transform method was developed by Li et al. (2013) to transform the non-uniform intensity values on spherical oranges into a uniform intensity values over the whole fruit surface. The frequency response of the Butterworth filter is maximally flat up to the cutoff frequency and after that it starts decreasing. They found that a ratio method and R and G component combination coupled with a big area and elongated region removal algorithm (BER) could be used to discriminate stem-ends from defects effectively. Mehl et al. (2002) presented multispectral techniques using hyperspectral image analysis for the detection of defects on three apple cultivars: Red Delicious, Golden Delicious, and Gala. They performed two steps: (1) designed multispectral imaging system from hyperspectral image analysis to characterize spectral features of apples for the specific selection of filters and (2) multispectral imaging for fast detection of apple contaminations. They worked with 153 samples and found good separation between normal and contaminated apples. However, separations found limited for Red Delicious. Mehl et al. (2004) also developed a hyperspectral imaging technique for the detection of apple surface defects and contaminations. Li et al. (2002) developed an apple surface defect sorting experimental hardware system based on computer image technology. The hardware system can inspect simultaneously four sides of each apple on the sorting line. They also developed the methods for image background removal, defects segmentation and identification of stem-end and calyx areas. Their results show that the experimental hardware system is practical and feasible. In current citrus manufacturing industries, color and calliper are key features for the automatic classification of fruits using computer vision approaches. However, human inspection is still the means to detect the flaws in the citrus surface. A computer vision system capable of detecting defects and also classifying the type of flaws in the citrus fruit is presented in (Lopez et al., 2011). Sobel gradient to the image is used to segment the faulty zones. Afterwards, color and texture features are extracted considering different color spaces. They employed several techniques for classification purpose and obtained promising results.

A synthesis segmentation algorithm is developed for the real-time online diseased strawberry images in the greenhouse (Ouyang et al., 2013). The impact of uneven illumination is eliminated through the “top-hat” transform, and noise interferences are removed by median filtering. They obtained complete strawberry fruit area of the image after applying the methods of gray morphology, logical operation, OTSU and mean shift segmentation. Then, they normalize the extracted eigenvalues, and used eigenvectors of samples for training the support vector machine and BP neural network. Their Results indicate that support vector machines have higher recognition accuracy than the BP neural network. Panli (2012) segmented the stem by mathematical morphology method firstly; then they applied attention selection model based on phase of the Fourier transform to extract the fruit saliency map, and fruit surface defects are detected; finally, support vector machine is used for the classification using the color and texture features of fruits defective part. They obtained the good classification accuracy.

Schatzki et al. (1997) has used the concept of X-ray imaging for defect detection in apples. Apples are characterized as infected or not based on the appearance in X-ray images. Human observers inspect sets of x-ray images for a given cultivar/orientation and the recognition rates recorded. When they viewed still images on a computer screen, they found acceptable recognition (= 50% of defective apples recognized, = 5% of good apples classified defective). Several thresholding and classification-based approaches are used for pixel-wise segmentation of ‘Jonagold’ apples surface defects. Segmentation accuracy improved when pixels are represented as a neighborhood (Unay, & Gosselin, 2006). According to the author, multi-layer perceptrons are more promising than the other techniques in terms of computational expense and segmentation accuracy. Their approach is much more precise on healthy fruit.

A fruit classification method based on a multi-class kernel support vector machine (kSVM) is proposed in (Zhang, & Wu, 2012). A split-and-merge algorithm is used to remove the background of each image; A feature space is composed from the extracted color histogram, texture and shape features of each fruit image; In order to reduce the dimensions of the feature space, principal component analysis (PCA) is used; The author constructed three kinds of multi-class SVMs, i.e., Directed Acyclic Graph SVM, Max-Wins-Voting SVM, and Winner-Takes-All SVM. They also chose three kinds of kernels, i.e., Gaussian Radial Basis kernel, Homogeneous Polynomial kernel, and linear kernel. Their results show that the Max-Wins-Voting SVM with Gaussian Radial Basis kernel reported the best classification accuracy of 88.2%. Tian et al. (2012) presented a Multiple Classifier System (MCS) based on the support vector machine for pattern recognition of wheat leaf diseases. Three different features including color, texture and shape are used as training sets. Firstly, these features are classified by the low-level of MCS classifier to different mid-level categories, which are partly described by the symptom of crop diseases. Then, from these mid-categories produced from low-level classifiers, the mid-level features are extracted. Finally, they trained the high-level SVMs which correct the errors made by the different feature SVMs to improve the performance of recognition. Their approach obtained a good success rate of recognition as compared with other classifiers for wheat leaf diseases.

3. PERFORMANCE COMPARISON

In this section, we compare the prominent surveyed methods for the fruit/fruit disease recognition system. Fig. 1 shows the flow diagram which operates in two phases, training and testing. Both require some preprocessing (i.e. image segmentation/defect segmentation and feature extraction). The system works in three steps, in the first step fruit images will be segmented into foreground and background in the case of fruit recognition while infected fruit part will be segmented from the diseased fruit image in the case of fruit disease recognition. In the second step feature extraction process is carried out. In the last step a

Multi-class support vector machine (MSVM) will be trained and fruits and vegetables will be classified into one of the classes or fruit diseases will be recognized using that trained MSVM.

3.1 Image Segmentation/ Defect Segmentation

Image segmentation is a convenient and effective method for detecting foreground objects in images with stationary background. Background subtraction is a commonly used class of techniques for segmenting objects of interest in a scene. This task has been widely studied in the literature. Background subtraction techniques can be seen as a two-object image segmentation and, often, need to cope with illumination variations and sensor capturing artifacts such as blur. Specular reflections, background clutter, shading and shadows in the images are major factors which must be addressed. Therefore, in order to reduce the scene complexity, it might be interesting to perform image segmentation focusing on the object's description only. We use a background subtraction method based on K-means clustering technique (Rocha et al., 2010). Amongst several image segmentation techniques, K-means based image segmentation shows a trade-off between efficient segmentation and cost of segmentation. Some examples of image segmentation are shown in figure 2.

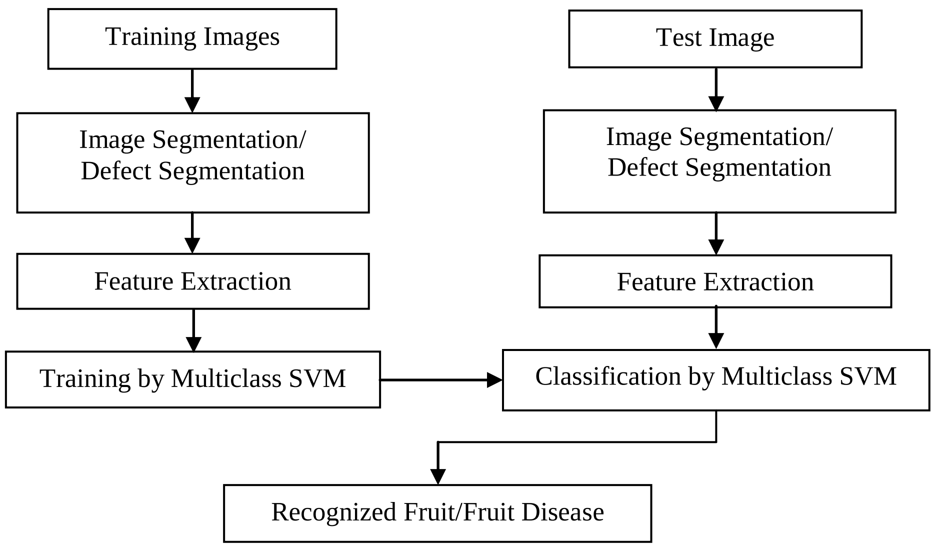

Figure 1. Fruit/Fruit Disease Recognition System. (*Dubey* & *Jalal*, *2012a*; *Dubey* & *Jalal*, *2012b*)

Figure 2. Some image segmentation result on fruit and vegetable images. (*Dubey* & *Jalal*, *2013*)

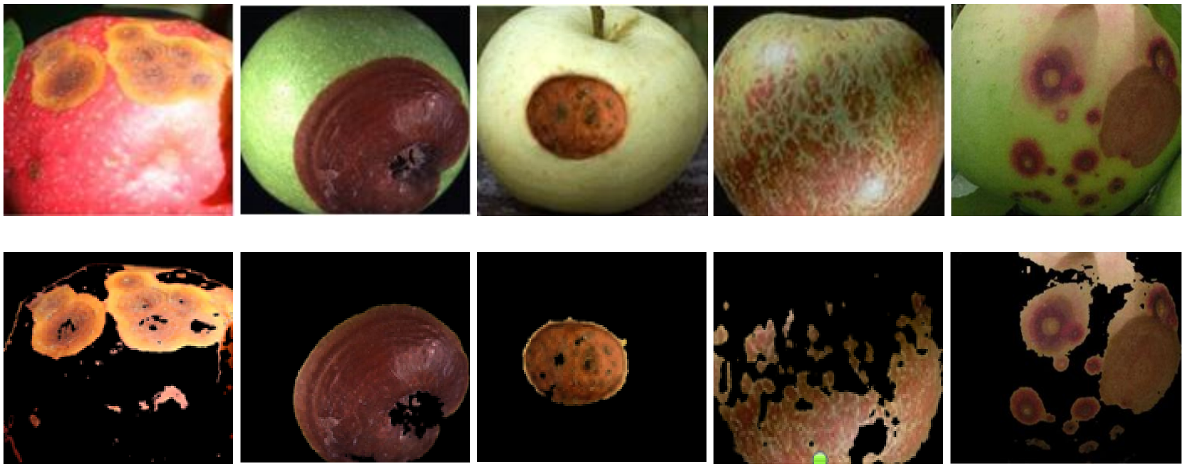

Figure 3. Some defect segmentation results on diseased fruit. (*Dubey* & *Jalal, 2012c*)

For the fruit disease classification problem, precise defect segmentation is required; otherwise the features of the non-infected region will dominate over the features of the infected region. K-means clustering technique is used for the defect segmentation of infected fruit images also but with three or four clusters, whereas in fruit background subtraction only two clusters are used. In defect segmentation, using only a single channel and two clusters are not sufficient, so here we use more than two clusters and consider more than one channel of the color images for the precise disease segmentation. In this experiment images are partitioned into three or four clusters in which one cluster contains the majority of the diseased parts. The final decision of the number of clusters is done by the empirical observation, i.e. once we defined that *c* number of clusters are sufficient for a particular problem then the further processing will not required the human intervention (i.e. fully automated). In our case, 2 and 4 number of clusters is set for the fruit classification and fruit disease classification problem respectively according to the source papers. Figure 3 depicts some image segmentation results using the K-mean clustering technique.

3.2 Feature Extraction

Some state-of-the-art color and texture features are extracted and used to validate the accuracy and efficiency of the system. The features used in the fruit and vegetable classification/fruit disease identification problem are Global Color Histogram, Color Coherence Vector, Border/Interior Classification, Local Binary Pattern, Completed Local Binary Patterns, Unser's Feature and Improved Sum and Difference Histogram.

1. Global Color Histogram (GCH)

The Global Color Histogram (GCH) is the simplest approach to encode the information present in an image (Gonzalez, & Woods, 2007). A GCH is a set of ordered values, for each distinct color, representing the probability of a pixel being of that color. Uniform normalization and quantization are used to avoid scaling bias and to reduce the number of distinct colors (Gonzalez & Woods, 2007).

2. Color Coherence Vector (CCV)

An approach to compare images based on color coherence vectors are presented by Pass et al., (1997). They define color coherence as the degree to which image pixels of that color are members of a large region with homogeneous color. These regions are referred as coherent regions. Coherent pixels are the parts of the contiguous region, whereas incoherent pixels are not. In order to compute the CCVs, the method blurs and discretizes the image's color-space to eliminate small variations between neighboring pixels. Then, it finds the connected components in the image in order to classify the pixels of a given color bucket is either coherent or incoherent. After classifying the image pixels, CCV computes two color histograms: one for coherent pixels and another for incoherent pixels. The two histograms are stored as a single histogram.

3. Border/Interior Classification (BIC)

In order to compute the BIC, the method classifies image pixels as border or interior. A pixel is classified as interior if its 4-neighbors (top, bottom, left, and right) have the same quantized color. Otherwise, it is classified as border. After the image pixels are classified, two color histograms are computed: one for border pixels and another for interior pixels (Stehling et al. 2002).

4. Local Binary Pattern (LBP)

Given a pixel in the input image, LBP is computed by comparing it with its neighbors (Ojala, Pietikainen, & Maenpaa, 2002):

$$LBP_{N,R} = \sum_{n=0}^{n-1} s(v_n - v_c)2^n, s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{1}$$

Where, v_c is the value of the central pixel, v_n is the value of its neighbors, R is the radius of the neighborhood and N is the total number of neighbors. Suppose the coordinate of v_c is (0, 0), then the coordinates of v_n are $(R\cos(2\pi n / N), R\sin(2\pi n / N))$. The values of neighbors that are not present in the image grids may be estimated by interpolation. Let the size of image is $I*J$. After the LBP code of each pixel is computed, a histogram is created to represent the texture image:

$$\begin{aligned} &H(k) = \sum_{i=1}^{I}\sum_{j=1}^{J} f(LBP_{N,R}(i,j),k), k \in [0,K], \\ &f(x,y) = \begin{cases} 1, x = y \\ 0, otherwise \end{cases} \end{aligned} \tag{2}$$

Where, K is the maximal LBP code value. In this experiment the value of 'N' and 'R' are set to '8' and '1' respectively to compute the LBP feature.

5. Completed Local Binary Pattern (CLBP)

LBP feature considers only signs of local differences (i.e. difference of each pixel with its neighbors) whereas CLBP feature considers both signs (S) and magnitude (M) of local differences as well as original center gray level (C) value (Guo, Zhang, & Zhang, 2010). CLBP feature is the combination of three features, namely CLBP_S, CLBP_M, and CLBP_C. CLBP_S is the same as the original LBP and used to code the sign information of local differences. CLBP_M is used to code the magnitude information of local differences:

$$CLBP_{N,R} = \sum_{n=0}^{n-1} t(m_n, c)2^n, t(x,c) = \begin{cases} 1, x \geq c \\ 0, x < c \end{cases} \tag{3}$$

Where, c is a threshold and set to the mean value of the input image in this experiment. CLBP_C is used to code the information of original center gray level value:

$$CLBP_{N,R} = t(g_c, c_I), t(x,c) = \begin{cases} 1, x \geq c \\ 0, x < c \end{cases} \tag{4}$$

Where, threshold c_I is set to the average gray level of the input image. In this experiment the value of 'N' and 'R' are set to '8' and '1' respectively to compute the CLBP feature.

Figure 4. Data set used in fruit and vegetable classification problem. (*Dubey & Jalal, 2013*)

Figure 5. Some images of scab, rot, blotch, and normal apples of dataset. (*Dubey & Jalal, 2012c*)

6. Unser's Feature (UNSER)

In order to extract the Unser feature, first the method finds the sum and difference of intensity values over a displacement of (d1, d2) of an image, then it calculates two histograms sum and difference histogram and stores both histograms as a single histogram (Unser, 1986).

7. Improved Sum and Difference Histogram (ISADH)

(Dubey, & Jalal, 2013) developed an efficient Improved Sum and Difference Histogram texture feature to encode the neighbouring information of a pixel in the image on the basis of sum and difference histogram. They first calculated sum and difference with neighbouring pixel in x-direction and then simulated these output in y-direction by calculating sum and difference in y-direction. By considering x and y direction separately, the algorithm is able to encode the relation of any pixel with its neighbouring pixels in both x and y direction very efficiently.

3.3 Training and Classification

Recently, a unified approach was presented in (Rocha et al., 2010) that can combine many features and classifiers. The author approached the multi-class classification problem as a set of binary classification problem in such a way one can assemble together diverse features and classifier approaches custom-tailored to parts of the problem. They define a class binarization as a mapping of a multi-class problem onto two-class problems (divide-and-conquer) and referred binary classifier as a base learner. For N-class problem $N \times (N-1)/2$ binary classifiers will be needed where N is the number of different classes. According to the author, the ij^{th} binary classifier uses the patterns of class i as positive and the patterns of class j as negative. They calculate the minimum distance of the generated vector (binary outcomes) to the binary pattern (ID) representing each class, in order to find the final outcome. Test case will belong to that class for which the distance between ID of that class and binary outcomes will be minimum.

Table 1. Unique ID of each class

	x*×*y	***x*×*z***	***y*×*z***
x	+1	+1	0
y	-1	0	+1
z	0	-1	-1

Their approach can be understood by a simple three class problem. Let three classes are *x*, *y*, and *z*. Three binary classifiers consisting of two classes each (i.e., *x*×*y*, *x*×*z*, and *y*×*z*) will be used as base learners, and each binary classifier will be trained with training images. Each class will receive a unique ID as shown in Table 1. To populate the table is straightforward. First, we perform the binary comparison *x*×*y* and tag the class *x* with the outcome +1, the class *y* with −1 and set the remaining entries in that column to 0. Thereafter, we repeat the procedure comparing *x*×*z*, tag the class *x* with +1, the class *z* with −1, and the remaining entries in that column with 0. In the last, we repeat this procedure for binary classifier *y*×*z*, and tag the class *y* with +1, the class *z* with -1, and set the remaining entries with 0 in that column, where the entry 0 means a "Don't care" value. Finally, each row represents unique ID of that class (e.g., *y* = [−1, +1, 0]). Each binary classifier results a binary response for any input example. Let's say if the outcomes for the binary classifier *x*×*y*, *x*×*z*, and *y*×*z* are +1, -1, and +1 respectively then the input example will belongs to that class which have the minimum distance from the vector [+1, -1, +1]. So the final answer will be given by the minimum distance of

$$\min\ \text{dist}\left(\{+1,-1,+1\},\left(\{+1,+1,0\},\{-1,0,+1\},\{0,-1,-1\}\right)\right)$$

We have used Multi-class Support Vector Machine (MSVM) as a set of binary Support Vector Machines (SVMs) for the training and classification in both problems.

3.4 Reported Results

To demonstrate the performance of the system, a supermarket data set of fruits and vegetables are used, which comprises 15 different categories: Plum(264), Agata Potato(201), Asterix Potato(181), Cashew(210), Onion(75), Orange(103), Taiti Lime(104), Kiwi(157), Fuji Apple(212), Granny-smith Apple(155), Watermelon(192), Honeydew Melon(145), Nectarine(247), Spanish Pear(158), and Diamond Peach(211): totaling 2615 images. Figure 4 depicts the classes of the data set. The data set contains fruit images under different lighting conditions with variability in the number of elements in an image. It also contains the pose differences among the fruits and cropping and partial occlusion. The presence of these features makes the data set more realistic. A data set of diseased apple fruits are also considered, which comprises four different categories: Apple Blotch (104), Apple rot (107), Apple scab (100), and Normal Apples (80): totaling 391 images. Figure 5 depicts the classes of the data set. The presence of a lot of variations in the type and color of apple makes the data set more realistic. In the experiment, different number of images per class is used for the training purpose. The average error is computed by calculating the sum of the average error of each class divided by the total number of classes. Figure 6 shows the average error for the fruit and vegetable classification for different features in both RGB and HSV color spaces while Figure 7 represents the average diseased apple fruit classification accuracy. The x-axis represents the number of images per class for the training and y-axis represents the average error/average accuracy. The result illustrates that the Global Color Histogram (GCH) has the highest average error in Figure 6 and lower average accuracy in Figure 7 for both RGB and HSV color images because, it has only the color information and it does not consider the relation among the neighboring pixels.

The average error for the Color Coherence Vector (CCV) is less than the average error for the GCH feature in Figure 6 and average accuracy of CCV is better than GCH in Figure 7 because CCV feature exploits the concept of coherent and incoherent regions. Border/Interior Classification (BIC) feature has low average classification error than the CCV feature because BIC feature takes the values of 4-neighboring pixel into account. UNSER feature has the lower average classification error than GCH, CCV, and BIC and higher classification than GCH and CCV as shown in Figure 6. For instance, the reported error for fruit and vegetable classification in RGB color space is 9.43%, 7.58%, 5.84%, 5.65%, and 4.56% for GCH, CCV, BIC, UNSER, and ISADH feature respectively while MSVM is trained with 60 images per fruit/vegetable. LBP feature in Figure 7 performs better than GCH and CCV because LBP incorporates the neighboring information in a rotation invariant manner. From Figure 7, CLBP (a generalized version of LBP) performs very well in both the color spaces. It is also observed across the plots that each feature performs better in the HSV color space than the RGB color space. For ISADH feature with 60 training examples per class, the reported classification error is 4.56% in RGB and 1.48% in HSV of fruit and vegetable classification. Figure 6 illustrates that the ISADH texture feature outperforms the other features because ISADH feature uses the neighboring information of x-direction with the neighboring information about y-direction. It is also pointed out that, for disease recognition problem CLBP is a better choice.

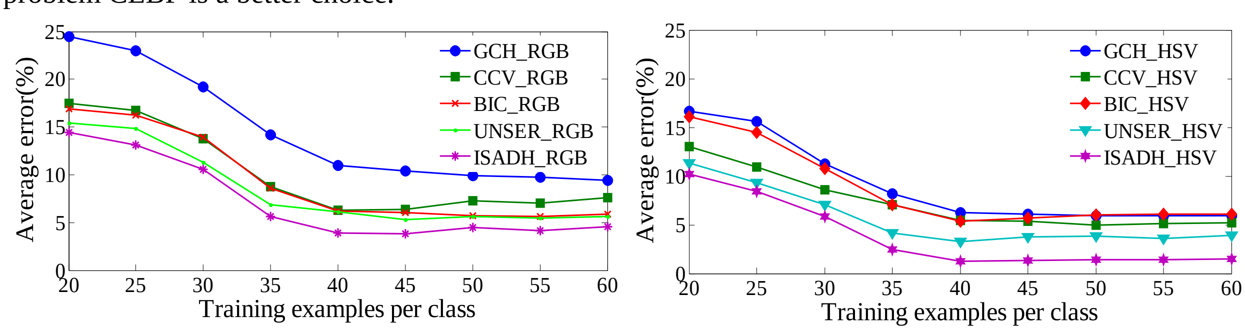

Figure 6. Average fruit and vegetable classification error by using GCH, CCV, BIC, UNSER, and ISADH features considering MSVM as a base learner in RGB and HSV color spaces. (*Dubey & Jalal, 2013*)

We also shown the comparison made to depict the performance of SVM and KNN classifiers using ISADH texture features in both RGB and HSV color spaces. In Figure 8, the comparison is illustrated for the fruit and vegetable classification problem. In Figure 9, the results are compared for the fruit disease recognition problem. The value K is considered as one in the source paper. It is observed across the plots that the performance using SVM classifier is better as compared to the well known KNN classifier in both RGB and HSV classifier. From the above reported results from various research papers, we can say that ISADH texture feature better suited with MSVM in both RGB and HSV color spaces to solve the both kinds of problem stated in this review paper.

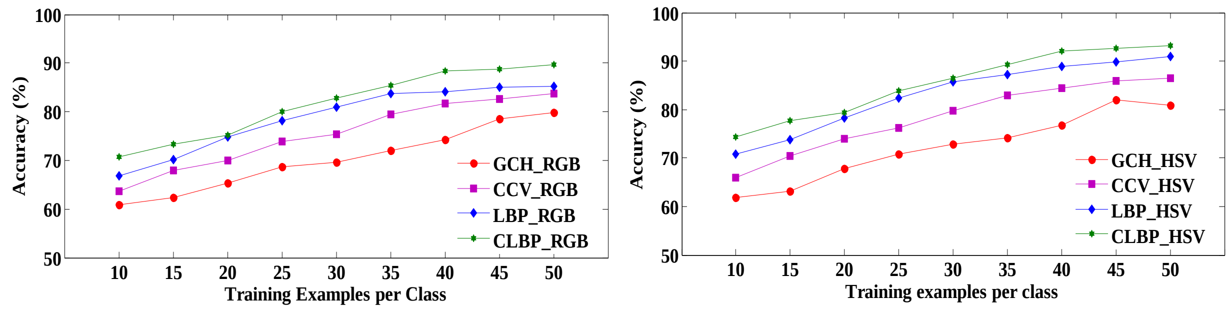

Figure 7. Apple fruit disease average classification accuracy by using GCH, CCV, LBP, and CLBP feature considering MSVM as a base learner in RGB and HSV color spaces. (*Dubey* & *Jalal, 2012c*)

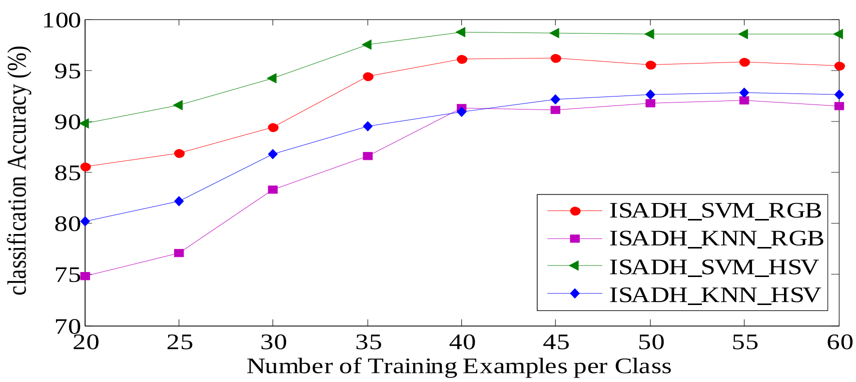

Figure 8. Comparison of SVM and KNN classifier using ISADH texture feature in RGB and HSV color spaces for fruit and vegetable classification problem (Dubey & Jalal, 2013)

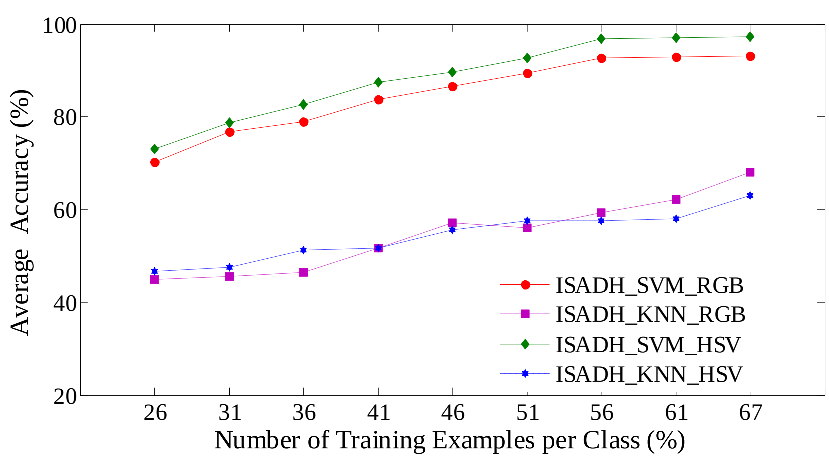

Figure 9. Comparison of SVM and KNN classifier using ISADH texture feature in RGB and HSV color spaces for fruit disease recognition problem (Dubey & Jalal, 2014)

3.5 Comparison among existing methods

We also compared the performance of different approaches reported in the literature in Table 2 and Table 3 to solve the fruit and vegetable classification and fruit disease recognition problem respectively. The comparisons are made on the basis of the number of categories in the database, pre-processing steps involved, features extracted, color space used, classifiers used, and accuracy achieved.

Table 2. Comparison with existing fruit and vegetable classification methods

Reference	Data set	Pre-Processing	Features	Color Space	Training	Evaluation Criteria	Average Accuracy
Dubey & Jalal (2013)	15 categories	K-means with 2 clusters	ISADH	HSV	Multiclass SVM	Accuracy	99%
Rocha et al. (2010)	15 categories	K-means with 2 clusters	GCH+CCV+BIC+Unser (Fusion)	HSV	Multiclass SVM	Average Error	97%
Arivazhagan et al. (2010)	15 categories	Cropping	Co-occurrence features such as contrast, energy, local homogeneity, cluster shade and cluster prominence	HSV	Minimum distance classifier	Recognition rate	86%
Chowdhury et al. (2013)	10 categories	-	Color Histogram +Texure	HSV	Neural networks	Accuracy	96.55%
Faria et al. (2012)	15 categories	K-means with 2 clusters	Color, Texture and Shape	HSV	Classifier Fusion	Accuracy	98.8% ± 0.9
Danti et al. (2012)	10 categories	Cropping and resizing	Mean and range of Hue and Saturation	HSV	BPNN Classifier	Accuracy	96.40%
Suresha et al. (2012)	8 categories	Watershed segmentation	Texture fearures	RGB	Decision-tree classifier	Accuracy	95%

Table 3. Comparison of existing methods for fruit disease recognition

Reference	Data set	Pre-Processing	Features	Color Space	Training	Evaluation Criteria	Average Accuracy
Dubey & Jalal (2014)	4 categories	K-means with 3 and 4 clusters	ISADH + Gradient filters	HSV	Multiclass SVM + KNN	Accuracy and AUC	>99%
Pujari et al. (2013a)	2 categories - Normal and affected anthracnose fruit types	K-means	Texture features	RGB	BPNN Classifier	Accuracy	84.65% for normal type and 76.6% for anthracnose affected type
Pujari et al. (2013b)	2 categories - Normal and affected fruit types	-	Color features+GLCM	YCbCr	BPNN Classifier	Accuracy	89.15% for normal type 88.58% for affected type
Pujari et al. (2014)	6 categories	Shade correction, Removing artifacts and Formatting	Color+Texture features	RGB	ANN/Knowledge base Classifier	Accuracy	87.80%
Kim et al. (2009)	6 categories	ROI Cropping	Intensity texture features	HSV	Discriminant Analysis	Accuracy	96%
Pydipati et al. (2006)	4 categories	Edge detection	Color co-occurrence methods	HSV	Generalized Squared Distance	Accuracy	>95%
Kanakaraddi et al. (2014)	4 categories	Median filtering	Color features	RGB	Decision tree	Disease severity	-

4. CONCLUSION

This paper basically reviewed the advancement of the information and communication technology in the field of agriculture and food industry. Several computer vision and image processing approaches used in the field of agriculture and food industry for fruit/vegetable classification and fruit disease classification is explored in this paper. Most of the work in this field using image processing is composed of the mainly three main steps (1) background subtraction, (2) feature extraction, and (3) training and classification. An image processing based solution is also explored from the published literature for automatic fruit/vegetable recognition and classification and automatic detection and recognition of fruit diseases from images using color and texture features. This approach is composed of three steps: in the first step image segmentation/defect segmentation is carried out using K-Means clustering method, in the second step features are extracted from the segmented image/defected region, and finally in the third step images are classified into one of the classes of fruit/fruit diseases. 15 types of fruits or vegetables and three types of apple diseases are used for the evaluation purpose. Based on the reported results, around 1% average classification error is detected for fruit and vegetable classification and around 3% average classification error is reported for fruit disease classification.

In the current work of fruit and vegetable classification and fruit disease recognition, only a single type of fruit and a single type of disease is present in the fruit or an infected fruit image. In the future, we will extend our work fruit and vegetable classification such that we can also identify the fruits and vegetables if more than one type is present in a single image. We may also try to identify all the diseases in the fruit if more than one disease is present in the image. The other future work includes the implementation of such systems in real life scenarios. Consideration of the shape feature with the color and texture features may also improve the classification accuracy.

REFERENCES

Arivazhagan, S., Shebiah, R. N., Nidhyanandhan, S. S., & Ganesan, L. (2010). Fruit recognition using color and texture features. *Journal of Emerging Trends in Computing and Information Sciences*, *1*(2), 90-94.

Arefi, A., Motlagh, A. M., Mollazade, K., & Teimourlou, R. F. (2011). Recognition and localization of ripen tomato based on machine vision. *Asian Journal of Crop Sciences, 5*(10), 1144-1149.

Bennedsen, B. S., & Peterson, D. L. (2005). Performance of a system for apple surface defect identification in near-infrared images. *Biosystems Engineering, 90*(4), 419–431.

Bennedsen, B. S., Peterson, D. L., & Tabb, A. (2005). Identifying defects in images of rotating apples. *Computers and Electronics in Agriculture*, *48*(2), 92–102.

Bolle, R. M., Connell, J. H., Haas, N., Mohan, R., & Taubin, G. (1996). Veggievision: A Produce Recognition System. In *Proceedings of the 3rd IEEE Workshop on Applications of Computer Vision* (pp. 1-8), Sarasota, USA.

Brosnan, T., & Sun, D. -W. (2002). Inspection and grading of agricultural and food products by computer vision systems - a review. *Computers and Electronics in Agriculture*, *36*(2-3), 193–213.

Brosnan, T., & Sun, D. -W. (2004). Improving quality inspection of food products by computer vision – a review, *Journal of Food Engineering, 61*(1), 3–16.

Bulanon, D. M., Burks, T. F., & Alchanatis, V. (2008). Study of temporal variation in citrus canopy using thermal imaging for citrus fruit detection. *Biosystems Engineering*, *101*(2), 161-171.

Bulanon D.M., Burks T.F., & Alchanatis V. (2009a). Image Fusion of visible and thermal images for fruit detection. *Biosystems Engineering, 103*(1), 12-22.

Bulanon, D. M., Burks, T. F. & Alchanatis, V. (2009b). Improving fruit detection for robotic fruit harvesting. *ISHS Acta Horticulturae 824: International Symposium on Application of Precision Agriculture for Fruits and Vegetables* (pp. 329-336).

Chowdhury, M. T., Alam, M. S., Hasan, M. A., & Khan, M. I. (2013). Vegetables detection from the glossary shop for the blind. *IOSR Journal of Electrical and Electronics Engineering, 8*(3), 43-53.

Crowe, T. G., & Delwiche, M. J. (1996a). Real-time defect detection in fruit - part I: Design concepts and development of protoype hardware, *Transactions of American Society of Agricultural and Biological Engineers*, *39*(6), 2299–2308.

Crowe, T. G., & Delwiche, M. J. (1996b). Real-time defect detection in fruit - part II: An algorithm and performance of a protoype system, *Transactions of American Society of Agricultural and Biological Engineers*, *39*(6), 2309–2317.

Danti, A., Madgi, M., & Anami, B. S. (2012). Mean and range color features based identification of common Indian leafy vegetables. *Int J Signal Process Image Process Pattern Recogn*, *5*(3), 151-160.

Dale, L. M., Thewis, A., Boudry, C., Rotar, I., Dardenne, P., Baeten, V., & Piernac, J. A. F. (2013). Hyperspectral Imaging Applications in Agriculture and Agro-Food Product Quality and Safety Control: A Review. *Applied Spectroscopy Reviews, 48*(2), 142-159.

Dubey, S. R. (2012). *Automatic Recognition of Fruits and Vegetables and Detection of Fruit Diseases*. Unpublished master's theses, GLA University Mathura, India.

Dubey, S. R., & Jalal, A. S. (2012a). Robust Approach for Fruit and Vegetable Classification. *Procedia Engineering, 38*, 3449 – 3453.

Dubey, S. R., & Jalal, A. S. (2012b). Detection and Classification of Apple Fruit Diseases using Complete Local Binary Patterns. In *Proceedings of the 3rd International Conference on Computer and Communication Technology* (pp. 346-351), MNNIT Allahabad, India.

Dubey, S. R., & Jalal, A. S. (2012c). Adapted Approach for Fruit Disease Identification using Images. *International Journal of Computer Vision and Image Processing, 2*(3), 51 – 65.

Dubey, S. R., & Jalal, A. S. (2013). Species and Variety Detection of Fruits and Vegetables from Images. *International Journal of Applied Pattern Recognition, 1*(1), 108 – 126.

Dubey, S. R., & Jalal, A. S. (2014). Fruit Disease Recognition using Improved Sum and Difference Histogram from Images. *International Journal of Applied Pattern Recognition*, *1*(2), 199 - 220.

Faria, F. A., dos Santos, J. A., Rocha, A., & Torres, R. S. (2012). Automatic classifier fusion for produce recognition. In *Proceeding of 25th SIBGRAPI Conference on Graphics, Patterns and Images* (pp. 152-259).

Fernando, L. -G., Gabriela, A. –G., Blasco, J., Aleixos, N., & Valiente, J. –M. (2010). Automatic detection of skin defects in citrus fruits using a multivariate image analysis approach. *Computers and Electronics in Agriculture. 71*(2), 189-197.

Gabriel, A. L. V., & Aguilera, J. M. (2013). Automatic detection of orientation and diseases in blueberries using image analysis to improve their postharvest storage quality. *Food Control, 33*(1), 166–173.

Gonzalez, R., & Woods, R. (2007). *Digital Image Processing, 3rd edition*, Prentice-Hall.

Guo, Z., Zhang, L., & Zhang, D. (2010). A Completed Modeling of Local Binary Pattern Operator for Texture Classification. *IEEE Transactions on Image Processing*, 19(6), 1657-1663.

Haidar, A., Dong, H., & Mavridis, N. (2012). Image-based date fruit classification. In *Proceedings of the 4th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops* (pp.357-363).

Hartman, J. (2010). Apple Fruit Diseases Appearing at Harvest. *Plant Pathology Fact Sheet*, College of Agriculture, University of Kentucky. Retrieved December, 2012, from http://www.ca.uky.edu/agcollege/plantpathology/ext_files/PPFShtml/PPFS-FR-T-2.pdf

Jimenez, R., Jain, A. K., Ceres, R., & Pons, J. L. (1999). Automatic fruit recognition: A survey and new results using Range/Attenuation images. *Pattern Recognition, 32* (10), 1719-1736.

Kanakaraddi, S., Iliger, P., Gaonkar, A., Alagoudar, M., Prakash A., (2014). Analysis and Grading of Pathogenic Disease of Chilli Fruit using Image Processing. In *Proceedings of the International Conference on Advances in Engineering & Technology* (pp. 46-50).

Kim, D. G., Burks, T. F., Qin, J., & Bulanon, D. M. (2009). Classification of grapefruit peel diseases using color texture feature analysis. *International Journal of Agricultural and Biological Engineering*, *2*(3), 41-50.

Kim, M. S., Lefcourt, A. M., Chao, K., Chen, Y. R., Kim, I., & Chan, D.E. (2002a). Multispectral detection of fecal contamination on apples based on hyperspectral imagery: Part I. application of visible and near-infrared reflectance imaging. *Transactions of American Society of Agricultural Engineers, 45*(6), 2027–2037.

Kim, M. S., Lefcourt, A. M., Chen, Y. R., Kim, I., Chan, D. E., & Chao, K. (2002b). Multispectral detection of fecal contamination on apples based on hyperspectral imagery: Part II. Application of hyperspectral fluorescence imaging. *Transactions of American Society of Agricultural Engineers, 45*(6), 2039–2047.

Kleynen, O., Leemans, V., & Destain, M. -F. (2005). Development of a multi-spectral vision system for the detection of defects on apples. *Journal of Food Engineering*, *69*(1), 41–49.

Leemans, V., Magein, H., & Destain, M. -F., (1998). Defect segmentation on 'golden delicious' apples by using colour machine vision. *Computers and Electronics in Agriculture, 20*(2), 117–130.

Leemans, V., Magein, H., & Destain, M. -F., (1999). Defect segmentation on 'jonagold' apples using colour vision and a bayesian classification method. *Computers and Electronics in Agriculture, 23*(1), 43–53.

Li, Q., Wang, M., & Gu, W. (2002). Computer Vision Based System for Apple Surface Defect Detection. *Computers and Electronics in Agriculture*, *36*(2-3), 215-223.

Li, J., Rao, X., Wang, F., Wu, W., & Ying, Y. (2013). Automatic detection of common surface defects on oranges using combined lighting transform and image ratio methods. *Postharvest Biology and Technology, 82*, 59–69.

Lino, A. C. L., Sanches, J., & Fabbro, I. M. D. (2008). Image processing techniques for lemons and tomatoes classification. *Bragantia*, *67*(3), 785-789.

Liu, Y., Chen, B., & Qiao, J. (2011). Development of a machine vision algorithm for recognition of peach fruit in natural scene. *Transactions of American Society of Agricultural and Biological Engineers, 54*(2), 695-702.

Lopez, J. J., Maximo, C. & Emanuel, A. (2011). Computer-based detection and classification of flaws in citrus fruits. *Neural Computing and Applications, 20*(7), 975-981.

Lorente, D., Aleixos, N., Gómez-Sanchis, J., Cubero, S., García-Navarrete, O. L., & Blasco, J. (2012). Recent Advances and Applications of Hyperspectral Imaging for Fruit and Vegetable Quality Assessment. *Food and Bioprocess Technology, 5*(4), 1121-1142.

Lu, R. (2003). Detection of bruises on apples using near-infrared hyperspectral imaging. *Transactions of American Society of Agricultural Engineers*, *46*(2), 523–530.

Mehl, P. M., Chao, K., Kim, M., & Chen, Y. R. (2002). Detection of defects on selected apple cultivars using hyperspectral and multispectral image analysis. *Applied Engineering in Agriculture, 18*(2), 219–226.

Mehl, P. M., Chen, Y. -R., Kim, M. S., & Chen, D.E. (2004). Development of hyperspectral imaging technique for the detection of apple surface defects and contaminations. *Journal of Food Engineering, 61*(1), 67–81.

Ojala, T., Pietikäinen, M., & Mäenpää, T. T. (2002). Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Pattern. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(7), 971-987.

Ouyang, C., Li, D., Wang, J., Wang, S., & Han, Y. (2013). The Research of the Strawberry Disease Identification Based on Image Processing and Pattern Recognition. *Computer and Computing Technologies in Agriculture VI, 392*, 69-77.

Panli, H. E. (2012). Fruit Surface Defects Detection and Classification Based on Attention Model. *Journal of Computational Information Systems, 8*(10), 4233–4240.

Pass, G., Zabih, R., & Miller, J. (1997). Comparing Images Using Color Coherence Vectors. In *Proceedings of the ACM Multimedia* (pp. 1-14).

Patel, H. N., Jain, R. K., & Joshi, M. V. (2011). Fruit Detection using Improved Multiple Features based Algorithm. *International Journal of Computer Applications 13*(2), 1–5.

Patrasa, A., Bruntona, N. P., Downeya, G., Rawsona, A., Warrinerb, K., & Gernigonc, G. (2011). Application of principal component and hierarchical cluster analysis to classify fruits and vegetables commonly consumed in Ireland based on in vitro antioxidant activity. *Journal of Food Composition and Analysis, 24*(2), 250–256.

Pujari, J. D., Yakkundimath, R., & Byadgi, A. S. (2013a). Grading and classification of anthracnose fungal disease of fruits based on statistical texture features. *International Journal of Advanced Science and Technology*, *52*.

Pujari, J. D., Yakkundimath, R., & Byadgi, A. S. (2013b). Reduced Color and Texture features based Identification and Classification of Affected and Normal fruits' images. *International Journal of Agricultural and Food Science, 3*(3), 119-127.

Pujari, J. D., Yakkundimath, R., & Byadgi, A. S. Recognition and classification of Produce affected by identically looking Powdery Mildew disease. *Acta Technologica Agriculturae*, *17*(2), 29-34.

Pydipati, R., Burks, T. F., & Lee, W. S. (2006). Identification of citrus disease using color texture features and discriminant analysis. *Computers and electronics in agriculture*, *52*(1), 49-59.

Qin, J., Burks, F., Ritenour, M. A., & Bonn, W. G. (2009). Detection of Citrus Canker using Hyper-Spectral Reflectance Imaging with Spectral Information Divergence. *Journal of Food Engineering*, *93*(2), 183-191.

Rahman, M. H., Pickering, M. R., Kerr, D., Boushey, C. J., & Delp, E. J. (2012). A New Texture Feature for Improved Food Recognition Accuracy in a Mobile Phone Based Dietary Assessment System. In *Proceedings of the IEEE International Conference on Multimedia and Expo Workshops* (pp. 418-423).

Roberts, M. J., Schimmelpfennig, D., Ashley, E., & Livingston, M. (2006). The Value of Plant Disease Early-Warning Systems: A Case Study of USDA's Soybean Rust Coordinated Framework. *Economic Research Service*, *18*, United States Department of Agriculture. Retrieved December, 2011, from http://www.ers.usda.gov/media/330972/err18_1_.pdf

Rocha, A., Hauagge, C., Wainer, J., & Siome, D. (2010). Automatic Fruit and Vegetable Classification from Images. *Computers and Electronics in Agriculture, 70*(1), 96-104.

Schatzki, T. F., Haff, R. P., Young, R., Can, I., Le, L. -C., & Toyofuku, N. (1997). Defect detection in apples by means of x-ray imaging. *Transactions of American Society of Agricultural Engineers*, 40(5), 1407–1415.

Seng, W. C., & Mirisaee, S.H. (2009). A new method for fruits recognition system. In *Proceedings of International Conference on Electrical Engineering and Informatics* (pp. 130-134).

Stehling, R., Nascimento, M., & Falcao, A. (2002). A Compact and Efficient Image Retrieval Approach Based on Border/Interior Pixel Classification. In *Proceedings of the ACM Conference on Information and Knowledge Management* (pp. 102-109).

Suresha, M., Sandeep Kumar, K. S., & Shiva Kumar, G. (2012). Texture Features and Decision Trees based Vegetables Classification. *IJCA Proceedings on National Conferecne on Advanced Computing and Communications* (pp. 21-26).

Tian, Y., Zhao, C., Lu, S., & Guo, X. (2012). SVM-based Multiple Classifier System for recognition of wheat leaf diseases. In *Proceedings of the World Automation Congress* (pp. 189-193).

Unay, D., & Gosselin, B. (2006). Automatic defect detection of 'jonagold' apples on multi-spectral images: A comparative study. *Postharvest Biology and Technology, 42*, (271-279).

Unser, M. (1986). Sum and Difference Histograms for Texture Classification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *8*(1), 118-125.

Vadivambal, R., & Jayas, D. S. (2011). Applications of Thermal Imaging in Agriculture and Food Industry—A Review. *Food and Bioprocess Technology, 4*(2), 186-199.

Zhang, Y., & Wu, L. (2012). Classification of fruits using computer vision and a multiclass support vector machine. *Sensors, 12*(9), 489-505.