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# VISIBLE IMAGE PROCESSING FOR FEATURE IDENTIFICATION AND CLASSIFICATION OF AGRICULTURAL PRODUCTS-A CRITICAL REVIEW REPORT

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**Abstract-**In this paper features like size, shape, and external defects of agricultural products were discussed. Major steps in image processing like enhancement, morphological operations, geometric features, pattern recognition and texture features were explained. Merits and demerits of classification techniques like support vector machine, linear discriminative analysis, fuzzy k-neural network, multilayer perceptron, mahalanobis distance classifier and learning vector quantization were furnished. The overall success of attempts on apples, potatoes was discussed. This paper is concluded with the critical remarks over the performance analysis of various techniques undertaken to carry-out the algorithm efficiencies.
**Keywords:** Image Processing, Features, Defects, Classification

## 1. INTRODUCTION

Manual grading of agricultural products based on size, shape and external defects leads to less efficiency. So there is a need to take a help of image processing for classification of agricultural products. This paper has been divided into four parts. First part emphasise the different important features of agricultural products. Second part explains feature extraction techniques in image processing. Third part explains different classifiers to classify agricultural products based captured images. Final step gives information of various successful attempts on classification of agricultural products.

## 2. DIFFERENT FEATURES OF AGRICULTURAL PRODUCTS

The various features which are recognized to grade agricultural products are size distribution, surface roughness, tuber germination, green spots, bruises and tuber disease due to viral, fungal or bacterial infection (Noordam et al. 2000). Although the most important quality parameters of a product include sensory attributes, nutritive values, chemical constituents, mechanical properties, functional properties and defects. The consumer's preferences depend primarily on the overall appearance, color and shape of the product (Elmasry et al. 2012).

Shape feature of an object refers to its profile and physical structure. These characteristics can be represented by boundary, region, moment, and structural representations. These representations can be used for matching shapes, recognizing objects, or for making measurements of shapes (Jain 2005). The size features can be used to represent an area property, and the compactness feature describes circularity. The feature vector can be used for object classification in to small, large, circular, non circular, small and circular, small and non circular, etc., (Milan et al. 2008). Size plays an important role in gradation of agricultural products (Amrinder and Kawaljeet 2016a). Shape and size are inseparable in a physical object and are both generally necessary if the object is to be generally described.

Round, oblate, unequal, truncate, oblong, conic and oblique are used to describe shape of apples based on longitudinal section. Regular, Irregular and ribbed are used to classify apples based on cross section. Round, oblong, ovate, oblique, oblate, elliptical, obovate and unequal are used to classify peaches based on longitudinal section. Oblate, round, elliptical and unequal are used to classify peaches based on cross section. Round, blocky and long are used to classify potatoes (Mohsenin 1986).

The line segment connecting farthest points is called the major axis of the boundary. The minor axis of the boundary is defined as the line perpendicular to the major axis. The ratio of the major to the minor axis is called the eccentricity of the boundary (Gonzalez et al. 2011).

Color is considered the most important visual attribute in the perception of product quality. The color of the food surface is the first quality parameter evaluated by consumers and is critical in acceptance of the product, even before it enters the mouth (Franco et al. 2006). Damage will also be considered as a feature for agricultural

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materials grading. Mechanical injuries will be in the form of cutting, peeling and bruising in the fresh fruits and vegetables. Crack is defined as the damage, resulting from the impact forces which may vary from complete splitting of the kernels to small hairline cracks invisible to the naked eye (Mohsenin 1986).
Grading is done usually based on: (i) physical characteristics like size, shape, colour, specific gravity, surface texture etc. (ii) biological characteristics like germination, insect damage and (iii) commercial value and usage (Singh et al. 2013). Grading of agricultural products is mostly done on the basis of its external appearance, mainly shape, color, texture and various external defects. With the rise in demand of quality agricultural products in market, grading and sorting becomes an essential asset to increase the revenue (Amrinder and Kawaljeet 2016a).
The objective of image processing was quality inspection, that is not usually practiced in the field during harvesting but has to be done in food processing industries along with post harvest processing line (Kiani and Minaei, 2016; Ayman et al., 2012; Mehrdad et al., 2015). Application of image processing to various items is furnished in Table 1.
Image processing technology is in a developing trend for qualitative inspection of food (Kiani and Minaei, 2016), detect external defects in apples (Ayman et al., 2012; Studman, 2001; Puchalski et al., 2008); figs sorting (Mehrdad et al., 2015); potatoes external defects (Hassankhani et al., 2012; Razmooy et al., 2012; Amrinder and Kawaljeet, 2016a; Debabrata et al., 2012; Jin et al., 2009; Caprara and Martelli, 2015); saffron quality checking (Kiani and Minaei, 2016) and biscuits crack inspection (Nashat et al., 2014; Bade et al., 2016).
Image processing was also used in estimating area and volume of eggs, lemons, limes and peaches (Sabliov et al., 2002), banana maturity assessment (Prabha and Kumar, 2015), berries yield prediction (Aquino et al., 2017), sorting of tomatoes (Mehrdad et al., 2012), evaluation of grape drying process (Nasser et al., 2013), banana size classification (Petingo and Bato, 2011), mango physical properties (Saad et al., 2015; Tomas, 2014), mango defect wise classification (Tomas, 2014), evaluating color of food surfaces (Yam and Papadakis, 2004), potato classification based on defects (Amrinder and Kawaljeet, 2016b), mango weight estimation (Spreer and Muller, 2011; Saad et al., 2015), leaf area estimation (Mora et al., 2016), and estimation of physic-chemical properties of sugarcane (Mohammad et al., 2017).
Image processing systems could match the high accuracy and speed demands of the current industry. As the demand for vegetables is rising day by day there is need for good quality batches. This is not only necessary for industrial requirements, but also for raw vegetables sale in the local market (Amrinder and Kawaljeet 2016a). Image processing involves the manipulation and interpretation of images, with the aid of images. It is a broad subject and it often involves procedures which can be mathematically complex (Lillisand et al. 2015).

## 3.1 MAJOR STEPS IN FEATURE EXTRACTION

**Image Enhancement**

Image enhancement technique includes mapping each gray level into another gray level by a predetermined transformation. This technique includes contrast stretching and histogram equalization. In histogram equalization, input gray levels are mapped so that the output gray level distribution is uniform. This has been found to be a powerful method of enhancement of low contrast images. Other enhancement techniques perform local neighbourhood operations as in convolution, transform operations as in the discrete Fourier transform, and other operations as in pseudo-colouring where a gray level image is mapped into a colour image by assigning different colours to different features (Jain 2005).
Image enhancement involves techniques for increasing the visual distinction between features in a scene. The objective is to create 'new' images from original image data in order to increase the amount of information that can be visually interpreted from data. The enhanced images can be displayed interactively on a monitor or they can be recorded in a hard copy format, either black and white or in a color. Various broad approaches to enhancement are manipulation of contrast of the image (level crossing and contrast stretching), spatial feature manipulation (spatial filtering, convolution, edge enhancement and fourier analysis), enhancement involving multiple spectral bands of imaginary (spectral rationing, principal and canonian components, vegetation compounds and intensity-hue-saturation color space transformations) (Lillisand et al. 2015).
Image enhancement refers to sharpening of image features such as edges, boundaries for display and analysis. Image enhancement includes gray level and contrast manipulation, noise reduction, edge crispening and sharpening, filtering, interpolation, magnification, and pseudocoloring. The greatest difficulty in image enhancement is quantifying the criterion for enhancement. Figure 1 lists common image enhancement techniques.
In image enhancement, the goal is to accentuate certain image features for subsequent analysis or for image display (Jain 2005). Visible image processing algorithm for a detect detection system includes two principal stages; the first is that a proper segmentation algorithm should be applied on the input image to separate purpose objects from background and the second consists of a proper defect detection algorithm which is used on the target objects (Razmjooy et al. 2012).

**3.2 Morphological Operations**

Morphology is a tool for extracting "meaning" from image components that are useful in the representation and description of region shape. Morphological techniques also include pre- or post processing, such as morphological filtering, thinning and pruning. Two fundamental morphological operations are dilation and erosion, in terms of union or intersection of an image with a translated shape called a structuring element. Combination of dilation and erosion will give more complex morphological operations. Morphological transformation involves two images, rather than a single image and a structuring element (Gonzalez et al. 2011). Morphological operations are used to help to define the image contours and eliminate or reduce noise (Razmjooy et al. 2012).

### 3.3 Geometrical Features

Geometrical features include perimeter, area, radii, number of holes, euler number, corners, bending energy, roundness or compactness and symmetry (Jain, 2005). These features include a number of descriptors that are useful when working with region boundaries. The length of boundary is one of its simplest descriptors. The length of a four connected boundary is defined as the number of pixels in the boundary, minus one. If the boundary is 8-connected, we count vertical and horizontal transitions as one and diagonal transitions as 1.414 (Gonzalez et al. 2011).

### 3.4 Pattern Recognition

Simplest machine vision tasks cannot be solved without the help of recognition. Recognition is the last step of the bottom up image processing approach. It is also often used in other control strategies for image understandings. Pattern recognition is used for region and object classification, and basic method of pattern recognition must be understood in order to study more complex machine vision processes (Milan et al. 2008).

### 3.5 Texture Features

Texture is observed in the structural patterns of surfaces of objects such as wood, grain, sand, grass, and cloth. The term texture generally refers to repetition of basic texture elements called *texels*. A texel contains several pixels, whose placement could be periodic, quasi-periodic or random. Natural textures are generally random, whereas artificial textures are often deterministic or periodic. Texture may be coarse, fine, smooth, granulated, rippled, regular, irregular, or linear. In image analysis, texture is broadly classified into two main categories, statistical and structural **(**Jain, 2005).

An important approach for describing a region is to quantify its texture content. Texture normally explained in terms of smooth, coarse and periodic texture. The histograms of these regions, obtained using function imhist. Texture will be computed based on statistical and spectral measures by using two custom functions and one tool box function. Statistical approaches frequently used for texture analysis is based on statistical properties of the intensity histogram. One class of such measures is based on statistical moments of intensity values. Custom function statxture, computes the texture measures (Gonzalez et al. 2011).

## 4. CLASSIFICATION TECHNIQUES

Classifier assigns classes to objects based on recognition. The parameters such as texture, specific weight, hardness, etc. are used for classification purpose. These parameters are called as pattern, and the classifier does not actually recognize objects, but recognizes their patterns. Object recognition and pattern recognition are considered synonymous. The main pattern recognition steps are finding an object, choosing elementary parameters or characteristics of the object, measuring the object parameters qualitatively or quantitatively. The outcome of pattern recognition is classification. Statistical object description uses elementary numerical descriptions called features. The pattern is also referred as pattern vector or feature vector (Milan et al. 2008). A major task after feature extraction is to classify the object into one of the several categories. Classification leads to segmentation, and vice-versa. Classification of pixels in an image is another form of component labelling that can result in segmentation of various objects in the image. Different classification techniques are given in Figure 2. Five classification methods, which are used to segment image, are linear discriminant analysis, k- nearest neighbours, naive bayes, decision trees and extreme learning machine (Rivera et al. 2014).

Support network of vectors is a training machine for classifying the input data into two groups but are also used for multi-class problems (Mehrdad et al. 2012). Support Vector machine (SVM) is a new state-of-the-art classification technique, which is based on the statistical learning theory and is designed to solve classification problems. It has been a powerful tool to perform non-linear regression, multivariate function estimation or non-linear regression. Main advantage of SVM is it does not need a large number of training samples for developing model and is not affected by the presence of outlier (Saad et al. 2015). Support Vector Machine (SVM) employs an optimal separating linear hyper-plane for data classification. It categorizes the data without knowing their distribution model and it does not require knowing the general structure of the problem. It turns into a new succession of classifiers and pattern recognition machines. This sort of classifier can be constructed by combination of two-class SVMs, and on contrary to other methods, this technique performs the classification between each class and the rest of classes (Mehrdad et al. 2012). The fundamental idea of supervises learning

algorithm (SVM) is to construct a hyper plane as a decision line, which separates the classes with the largest margin (Nashat et al. 2014).
Support Vector Machines (SVMs) are mathematical entity, an algorithm for maximizing a specific mathematical function with respect to a given collection of data. SVM theory will give better result than using only threshold for each channel. These are very popular for discrimination roles because they can accurately combine a lot of features to find an optimal separating hyper plane. It minimizes the error on the training set and maximizes the margin. Support vector machines new classifiers which are well known nowadays and are used for the comparisons. Advantage of SVMs is delivering a unique solution, since the optimality problem is complex. Support Vector Machine (SVM) demerits are (1) training is slow for large problems and (2) training algorithms are complicated, lacking significance and difficult to implement. New SVM learning algorithm i.e. sequential minimal optimization (SMO) is conceptually simple, easy to implement, often faster than standard SVM algorithm (Razmjooy et al. 2012).
The K-nearest- neighbourhood (k-nn) algorithm is a popular supervised classification algorithm and is defined as a nonparametric supervised pattern classification method (Razmjooy et al. 2012). Multi Layer Perceptron (MLP) neural networks are generally referred to as feed-forward multi-layer neural networks. In this, number of neurons in entry (input) and exit (output) layers are determined based on number of the respective data features and number of classes. These networks train the data based on two parameters namely, number of neurons in hidden layer and type of neuron transfer function (Mehrdad et al. 2012). Learning Vector Quantization (LVQ) networks classify input vectors into target classes using competitive layer, where input vectors are first classified as sub-classes and these sub-classes are then combined with each other and are placed into target classes. This has the capacity of classifying any set of input vectors (Mehrdad et al. 2012). Support Vector Machine (SVM) has a better performance compared to Multi Layer Perceptron (MLP) and Learning Vector Quantization (LVQ) in tomato classification (Mehrdad et al. 2012).
The benefits of neural network are the generalization authority on the untrained samples due to the massively parallel interconnections and ease of implementation simply by training with training samples for any complicated rule or mapping problem. Performance of neural network is authentic upon the assumption that we have enough data samples (Razmjooy et al. 2012). Operational time of SMO based SVM is 41.47 times quicker than K-nn, 5.36 times quicker than MLP, 2.70 times quicker than SVM-linear kernel, 5.09 times quicker than SVM-poly nominal kernel, 4.59 times quicker than SVM-quadratic kernel (Razmjooy et al. 2012). Principal Component Analysis (PCA) is a data compression technique and produces a linear combination of the variables (red, green, blue) which form improved descriptors for structure or patterns in the data and it has been used for the extraction of a training and test set (Noordam et al. 2000). Discriminant analysis (DA) is a supervised machine learning method to establish classification. The objective of DA learning is to identify a subset of observations into two or more groups (Saad et al. 2015). Mahalanobis distance classifier takes into account errors associated with prediction measurements, such as noise by using the feature covariance matrix to scale features according to their variances (Mery et al. 2013).

## Overall Success of Various Attempts on Different Agricultural Products

A system for identifying surface defects on potatoes was designed, based on acquired images, while potatoes were rotating in front of the camera. An algorithm was developed to detect defects. Along with defect detection, a simple size sorting is also applied. The developed algorithm method in classification has an accuracy of about 95 per cent and the size grading has an accuracy of 96.86 per cent (Razmjooy et al. 2012). Image processing was implemented to grade potatoes on size, shape and external defects. Linear Discriminative Analysis (LDA) and Multilayer Feed forward – Neural Network (MLF-NN) are used for colour sorting with 86.8 - 98.6 per cent and 88.1 - 99.2 per cent respectively **(**Noordam et al. 2000). The results showed that FuzzyARTMAP outperformed the Backpropagation and Perceptron models due to its stability and convergence speed with times as low as 1 ms per pattern which demonstrates its suitability for real-time inspection of misshapen potatoes (Rios et al. 2008)
A method was proposed for Apple defect detection and quality classification with Multi Linear Perceptron-Neural Networks. Color, texture and wavelet features are extracted from apple images. Principal component analysis was applied on the extracted features and some preliminary performance tests were done with single and multi layer perceptron **(**Gill et al. 2014). A system for apple defect detection was designed, based on analyzing images. Dark areas caused by defects would appear with almost the same shape and same place in three or more frames. The algorithm developed was able to detect defects such as bruises, frost damage, and scab. The method had a classification accuracy of 96 per cent for the samples (Puchalski et al. 2008).
One hundred and forty two tomato images at different light conditions were captured. Out of this eighty six samples were analyzed as training data and fifty six samples were used as test data set. Training data has 100 per cent accuracy for support vector machine compared to 80 per cent for multi layer perceptron and 93.4 per cent in linear vector quantization. Test data has 77 per cent accuracy for both multi layer perceptron and support vector machine, and 74.5 per cent for linear vector quantization (Mehrdad et al. 2012).
An algorithm has been implemented to measure size, roundness and percent defect of a mango. Nearest neighbour technique with Euclidean distance was used to determine the quality of the mango since the data

points cannot be easily separated (Tomas 2014). Mango quality has been inspected using machine vision which has 180 samples for training. Both the discriminative analysis and support vector machine have been investigated for shape analysis of mangoes. Hundred per cent classification has been achieved for support vector machine technique compared to discriminative analysis (Saad et al. 2015).

Apples, Tomatoes, Mangoes and Potatoes were successfully classified using classifiers based on size, shape and defects.

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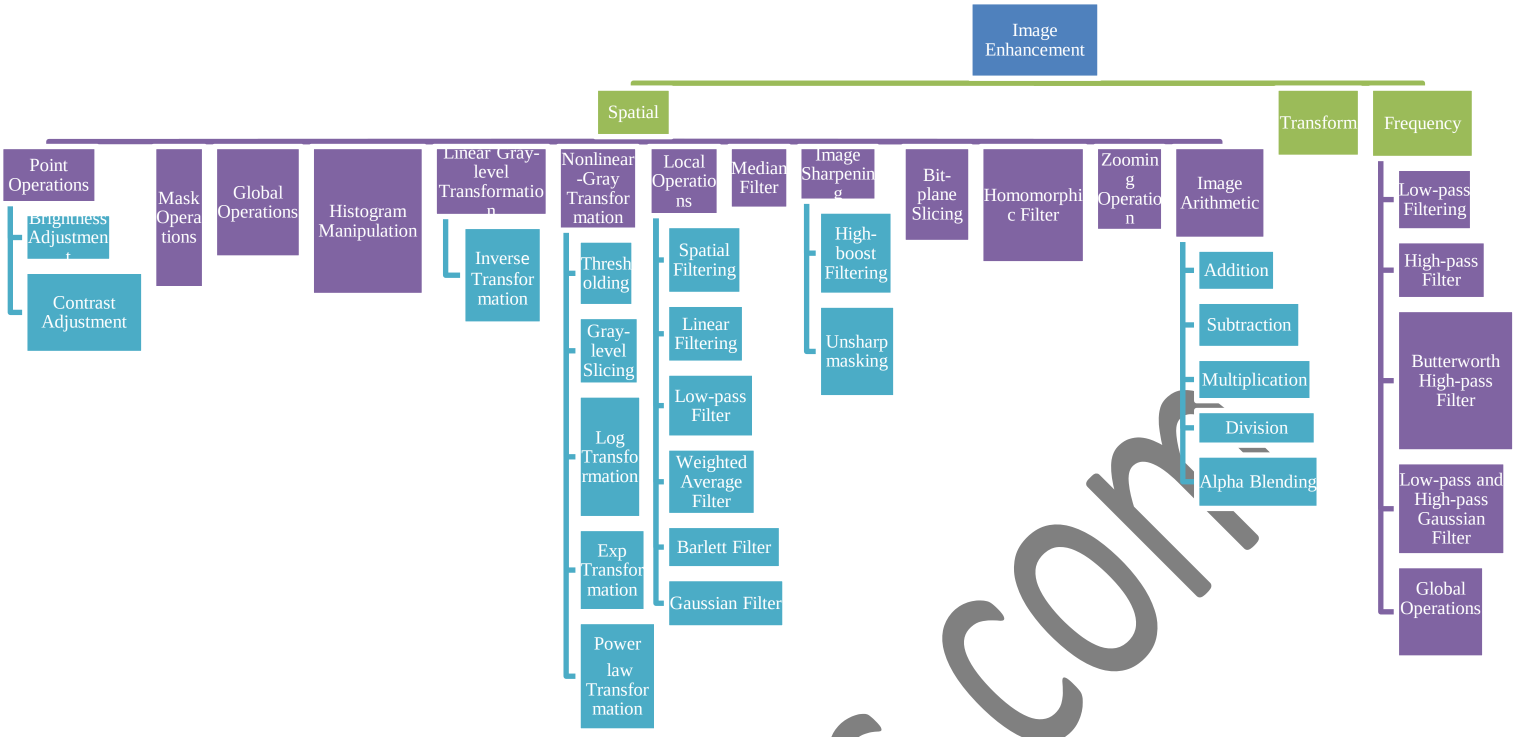


**Fig. 1. Methods of image enhancement**

*Source: (Jayaraman et al. 2012)

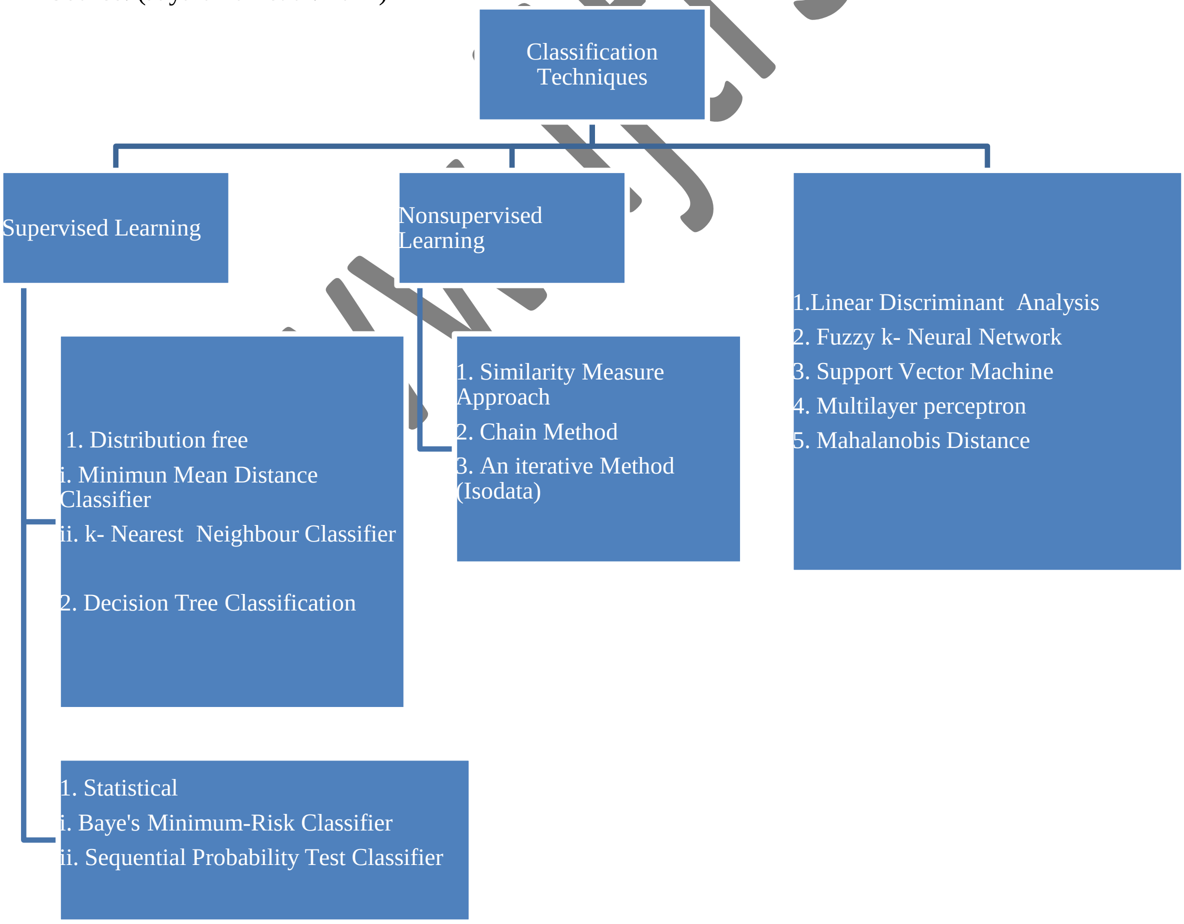


**Fig. 2. Different classification techniques**

*Source: Jain (2005)

**Table 1. Detailed Information of Image Processing Application to Agricultural Products**

| Application | Product | Software | Image size | Reference |
|---|---|---|---|---|
| Classification | Dried figs | Lab-VIEW | 640*480 | Mehrdad *et al.*, (2015) |
| Shape and weight estimation | Mangoes | Lab-VIEW | 1600*1200 | Saad *et al.*, (2015) |
| Defect wise sorting | Potato | Matlab | - | Hassankhani *et al.*, (2012) |
| External defect detection | Potato | Visual Studio | - | Amrinder and Kawaljeet, (2016a) |
| Defect inspection | Potato | Matlab | 4320*3240 | Razmooy *et al.*, (2012) |
| Quality checking | Saffron | - | - | Kiani and Minaei, (2016) |
| Quality evaluation | Pecans | Matlab | 1024*1022 | Nachiket *et al.*, (2007) |
| Segmentation of images | Potato | Matlab | - | Amrinder and Kawaljeet, (2016b) |
| Disease detection | Potato | - | - | Debabrata *et al.*, (2012) |
| Defect detection | Potato | - | - | Jin *et al.*, (2009) |
| External damage evaluation<br>Sorting based on size and color | Potato<br>Potato | IMAQ Vision Builder<br>Matlab | -<br>- | Caprara and Martelli, (2015)<br>Hassankhani and Navid, (2012) |
| Area and volume determination | Eggs, Lemons, Limes and Peaches | Matlab and Photoshop | - | Sabliov *et al.*, (2002) |
| Defect detection | Biscuits | Python and Open CV | - | Bade *et al.*, (2016) |
| Classification and sorting | Tomato | - | - | Mehrdad *et al.*, (2012) |
| Size classification | Banana | Visual Basic 6 | - | Petingco and Bato, (2011) |
| Maturity assessment | Banana | Matlab | 3072*2304 | Prabha and Kumar, (2015) |
| Physical properties | Apples, Mango, Melons and Orange | Matlab | 120*160 | Sahana and Anita, (2017) |
| Yield prediction | Berries | Matlab | 1170*1578 | Aquino *et al.*, (2017) |
| Defect detection | Apples | - | 1024*1024 | Puchalski *et al.*, (2008) |
| Modeling of drying process | Grapes | Matlab | - | Nasser *et al.*, (2013) |
| Physical properties and defect classification | Mangoes | Matlab | 640*480 | Tomas, (2014) |
| Physical and chemical properties | Sugarcane | Matlab | - | Mohammad *et al.*, (2017) |
| Weight estimation<br>Leaf area estimation<br>Color estimation | Mango<br>Trees<br>Pizza | -<br>-<br>Photoshop | -<br>2048*1536<br>1600*1200 | Spreer and Muller, (2011)<br>Mora *et al.*, (2016)<br>Yam and Papadakis, (2004) |