Section A-Research paper
ISSN 2063-5346

IMAGE PROCESSING BASED FRUIT DETECTION AND GRADING CLASSIFICATION SYSTEM: A REVIEW

Himanshu B. Patel[1], Nitin J. Patil[2]

[1]Department of Instrumentation Engineering, D. N. Patel College of Engineering, India.
E-mail: himanshu74patel@gmail.com

[2]Department of Instrumentation Engineering, D. N. Patel College of Engineering, India.
E-mail: nitinpatil2002@gmail.com

ABSTRACT

Automation is used to boost production, quality, and profitability for the nation. Fruit sorting and grading is an essential procedure for fruit producers since it impacts the quality of the fruit as well as the market for exports. Human grading and sorting are feasible; however, it is very time-consuming, labor-intensive, and a tedious work. As a result, an advanced fruit sorting and grading system are necessary. Using computer vision, researchers have developed several fruit sorting algorithms in recent years. The most frequent criteria used to detect illnesses, ripeness, and a class of fruits is color, textural, and morphological characteristics. Clustering and color-based segmentation, artificial neural networks, and other classifiers are some of the techniques used. The study of various fruit detection systems is the major focus of research work nowadays. These characteristics are then utilized to train a soft computing method network. This study examines the use of image processing in agriculture to give insight into the usage of vision-based systems by highlighting its benefits and drawbacks.

Keywords: Detection, image processing, Extraction, artificial neural network, Segmentation.

1. INTRODUCTION

It is important to have better fruit quality in today's modern period for human health, and this may be because fruits are graded according to their size, texture, color, or quality. Manual grading, on the other hand, needs a large quantity of manpower. To solve this, an automatic grading system is required for superior quality fruit grading. Non-destructive automated quality detection technology is required to enhance fruit quality detection. The method should also improve grading efficiency while lowering labor costs. Non-destructive fruit detection is the technique using image processing for detecting fruits from all sides without hurting them, utilizing detecting equipment to produce an assessment based on some common standards. Because of the inadequate process, it is now difficult to identify fruit form size or color, but utilizing vision detecting technology, It is now feasible to identify the right kind of fruit. Low efficiency, poor grading speed, high cost, and complexity affect the bulk of present fruit quality detection and grading systems. As a result, it's important to build a low-cost, high-speed, fruit size detection and grading system [1].

It is challenging to estimate mathematically, the data and information mainly collected from the images. The image processing has vide applications in the agriculture sector. In computer vision technology capture image, interpret and classify the parameter and an information furnish for fruit sorting and grading purposes. Various researchers have proposed [2], some of the researchers focus on various techniques, others on fruit quality analysis. In this review paper is to elaborate a comparable study of various pre-processing, image segmentation, features and classification techniques, and analysis of fruit quality on the basis of shape, color, texture, and size.

The paper is organized as follows: Section 2 discusses the different image processing techniques and presents the outcomes of different researchers. Section 3 explains sorting method of fruit. Finally, conclusions are given in section 4.

2. BASIC STAGES IN IMAGE PROCESSING

Fruit detecting and grading system with image processing technique having five stages[3], as represented in Fig. 1.

Stage1: Image Acquisition: This is the initial stage in image processing, in which a camera is used to capture digital fruit images and store them on any digital medium.
Stage2: Image Pre-processing: In this stage eliminates noise, smoothens the image, and also performs scaling of images. In addition to converting RGB images to grey images, the contrast of an image is enhanced to a certain extent.
Stage3: Image Segmentation: Segmentation is the process of separating an image into different segments.
Stage4: Feature Extraction: In this stage is used for finding different features like color, texture, and shape, which minimizes resources to define a big data set before the classification of the image.
Stage5: Classification: This part examines the numerical properties of image features and categorizes the information. It employs a neural network for fruit disease training and classification.

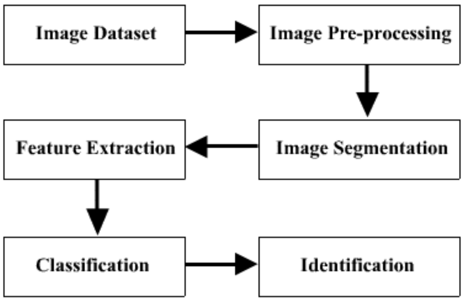

Figure. 1. Stages of image processing.

2.1. IMAGE ACQUISITION

Image capture techniques used in various applications include cameras, Magnetic Resonance Imaging (MRI), Ultrasound, Computer Tomography (CT), and Electrical Tomography. Image sensors such as Charged Coupled Device (CCD) and Complementary Metal-Oxide-Semiconductor (CMOS) are utilized to create a digital image. The five basic components of a conventional computer vision system are lighting, a digitizer image capturing board, a camera, and computer hardware. Fig. 2 shows computer vision system for image acquisition.

The light systems in the study of fruits are arranged in place of front and rear illumination. Front lighting is used to examine surface quality features such as color, texture, and skin flaws. Backlighting is specified to examine the border quality features such as size and form. For quality assessment of agricultural produce, conventional, hyper spectral, and multispectral computer image systems have been thoroughly characterized [3].

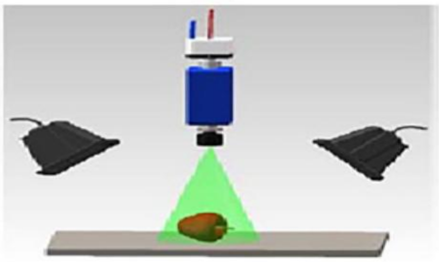

Figure. 2. A classical computer vision system

ISSN 2063-5346

2.2. PRE-PROCESSING

It efficiently shows or records data for further visual understanding. Image enhancement is a transformation technique conducted on a image to improve the quality and information of the image to meet the end requirements of users for a certain application. This procedure does not alter data in any way, but it does alter the dynamic range of particular characteristics for localization. The majority of pre-and post-processing algorithms are based on these image-enhancing approaches, it can be classified into two groups: Techniques in the spatial and frequency domains [4]. While spatial enhancement techniques conduct direct manipulations on image pixels, frequency enhancement techniques do indirect manipulations on images by transforming them using convolution or kernels. Fig. 3 shows preprocessing on fruit. Table 1 illustrates different pre-processing techniques with their advantages and disadvantages.

2.2.1 COLOR SPACE TRANSFORMATION (CST):

It is a widely used pixel pre-processing method for evaluating fruit quality. The majority of CST applications use the saturation, hue, and intensity (HSI) color space, wherein saturation produces a monochromatic image and conveys the image texture. It employs a basic filter to decrease noise, a median filter to decrease peak noise, and a modified unsharpened filter to decrease peak noise [5]. The Hue component is an angle between [0,360] degrees that specifies the color. The Saturation component specifies how much white light dilutes the color.

2.2.2 RGB:

A true-color image is one in which each pixel's Red, Green, and Blue color components are defined. This RGB array is of type double, with a value ranging from 0 to 1 for each color component. This can be stored in the third dimension of the data array.

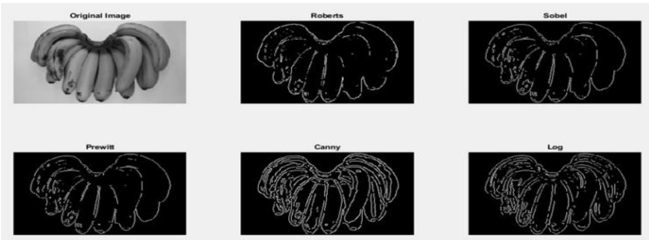

Figure. 3. Image recognition and pre-processing

Table 1. Pre-processing techniques and their advantages and disadvantages.

Filters	Advantages	Disadvantages
Median filter	Robust, Edges are better preserved, and salt and pepper noise is removed.	Gaussian noise has distorted the image.
Adaptive- Median filter	Decreased impulse response and distortions, as well as noise smoothing.	Less loss of data compared to the median.
Gaussian filter	Removes Gaussian noise effectively, Enhancement.	Take the time and simplify the specifics.
Weiner filter	De-noising is superior to the median.	The result is too hazy.
Adaptive histogramequalization	Noise is amplified too much.	Consuming more Time

2.3. SEGMENTATION

Image segmentation, which divides a digital image into discrete regions, is necessary after pre-processing. By various researcher in Table 2 illustrates fruit quality analysis on the basis of different segmentation techniques. Fig. 4 shows the segmentation techniques on banana fruit.

The technique of splitting a digital image into numerous pixels or segments is known as image

ISSN 2063-5346

segmentation. Because pixels in a given region are comparable in terms of color, intensity, texture, and other characteristics, it is possible to find and identify objects and boundaries in an image [6]. Filtering noisy images, biomedical applications (locate tumors, size tissue volumes, computer-guided surgery, diagnosis, treatment, planning, and study of the body structure), locate objects in satellite images; face recognition, fingerprint recognition, and so on are just a few of the many practical applications of image segmentation. Some segmentation strategies have been researched in the literature. Means is more realistic because noisy precise division does not occur in actual life.

Table 2. Segmentation techniques and their advantages and disadvantages

Method of Segmentation	Advantages	Disadvantages
Threshold Technique	• The concept is simple. • It may be used for real time applications. • Speed of operation is fast. • No prior knowledge is required.	• Because the spatial information of the images is not used, the image will have noise, fuzzy edges, and outliers. • Highly sensitive to noise. • Selection of threshold is crucial.
Region growing	• Separates the region of the same characteristics we specified appropriately. • Sharp edges indicate successful segmentation. • The premise is straightforward. • Its outcomes are well-matched in terms of form. • Has the ability to set seed points and criteria. • Ability to choose several criteria at the same time.	• Has a problem of consuming computational time. • Cannot differentiate the fine variation of the images.
Region merging and shifting	• We divide the image till we get the desired resolution. • The merging criterion and the splitting criteria might be different.	• There is a lot of computation. • It has a blocky segmentation issue.
Edge detection	• It is good for images to have better contrast between objects. • Having fixed characteristics.	• Sensitive to noise. • Time consuming. • Complex computation.
Segmentation based on clustering	• Produces good clusters and works well with tiny datasets. • Provides image into homogeneous cluster.	• Complexity. • Inability to recover from the database.
K-means clustering	• Quickness. • Because the number of clusters is set. • the concept is uncomplicated.	• The problem is choosing the number of clusters. • Various starting centroids will provide different outcomes.
Fuzzy C- means clustering	• When there is no crisp boundary of an image, then this technique is used for segmentation • Classify pixel value with good accuracy.	• Time-consuming. • In noisy images, it does not consider spatial information, making it susceptible to noise and other image distortions. • Sensitive to changes in light intensity. • The problem is in choosing the number of clusters.
Mask R-CNN	• General approach and Simple flexible • It is also state-of-the-art for image segmentation.	• Not accurate. • Mask quality always challenges.
Watershed segmentation	• Fast speed • The large no. of segmentation region results are reliable.	• Over segmentation • Over cutting, leaking.

ISSN 2063-5346

Ghabousian and Shamsi (2012) [8] present a fuzzy clustering technique for segmenting color images of apples that improves segmentation accuracy. This technique uses the color space L*a*b, which has the greatest segmentation properties of apple-colored images.

Figure. 4 Types of banana fruits segmented, and brown specks extracted. i) First column – input image, ii) Second column – segmentation mask, iii) Third column – segmented fruit, and iv) Fourth column – segmented fruit without brown spots.

Before the vision approach for image enhancement, a segmentation step with the Hough transform was implemented. The fruit and vegetable images were classified using the Nave Bayes classifier. For image segmentation, the suggested technique was automated using a texture-based approach [9]. The photos are gathered from all 360-degree angles in order to train the classifier for the most effective output. The classifier's feature vector is composed of fractal dimension and matrix-based characteristics taken from the grey level image.

The E-K-Means Clustering method proposed by Kanjana [10] is better to the other two techniques. The esteem of the Support Vector Machine algorithm ranges from 40.6 to 66.9, that of the Existing-K-Means neighbour technique ranges from 49.6 to 77.5, and that of the E-K-Means clustering algorithm ranges from 55 to 86. The E-K-Means clustering technique consistently produces great results.

Islam et al. [11] offer a method for detecting potato illnesses that combines machine learning and image segmentation. The data set of 300 potato plants, a publically accessible plant photo collection. To get ROI, the CIE method is used for color-based segmentation.Important characteristics are extracted using the GLCM feature. The model is evaluated on over 300 images, and it achieves a 95 percent efficiency by employing a segmentation strategy and a support vector machine.

Dah-Jye-Lee et al. [12] utilized color mapping to analyze the feature and ripeness stage of farm produce such as tomatoes and date fruits. The sort of dying method used to ripen dates and the amount of time the tomatoes may be carried are both determined by color. Color mapping is a technique that transforms a spectrum of 3-Dimensionalcolor to 1-Dimensionalcolor indices for automatic color classifying. It's a straightforward color grading method that works well.

Jay Prakash Gupta et al. [13] proposed a unique color-based fault segmentation of fruit using the K-mean clustering unsupervised technique. K-mean is a popular method for determining the natural pixels grouping in an image. It is a simple and quick approach. For the testing, the author utilized defective apples and assessed the recommended techniques. The proposed defect segmentation approach produces exact findings in a short amount of time. The previous work, which used several image processing algorithms, focused on the accuracy of fruit categorization and the time it took to obtain the findings.

Lingeswari et al [14] focused on early detection of tomato infections. The proposed system uses a variety of methodologies, including color thresholding segmentation algorithms and K-means clustering. In the suggested system, the K-means are shown. For the early diagnosis of tomato diseases, clustering outperforms the RGB color-based color threshold technique. However, there is also a requirement for reliable detection and categorization of fruit illnesses.

2.4 FEATURE EXTRACTION:

Feature extraction is a step in the dimension reduction process, which splits and minimizes a large set of raw data into smaller subgroups. As a result, processing will be simpler. The fact that these large data sets include numerous variables is the most important feature. A large amount of processing power is required to handle these variables. As a result, feature extraction supports the extraction of the best feature from large data sets by identifying and grouping variables into features, significantly reducing the quantity of data.

2.4.1 COLOR FEATURES:

In image retrieval and indexing, the color feature is the earliest and most commonly utilized visual feature. High efficiency, simplicity of extracting color data from photos, size and orientation independence, strong in portraying visually content of images, resilient against backdrop difficulties, and powerful in distinguishing images from one another are only a few of the benefits of the color feature. For color assessment of fruit and vegetable quality, the RGB color system, HSI color space, and CIE Lab color space are widely employed. Color features may be retrieved from images after the color spaces have been defined. Many researchers have introduced color characteristics such as color correlograms and color cohesion. Many studies offer different color qualities such as the color correlogram, color coherence vector, color moments, and color histogram, among others. One of them is the color moment, which is both simple and effective. The most common moments are the mean, standard deviation, and skewness [15].

People use the HSV color space to choose colors from a color wheel or palette. H stands for Hue, which denotes color; S stands for Saturation, which denotes shadow; and V is for Value, which denotes tone. Hue, saturation, and intensity are the three components of HSI color space. HSI color space is the greatest tool for creating image processing algorithms that are based on realistic and human-perceived color. The study first discusses image's histogram is calculated. In the network, illnesses are classified using an ANN neural network and a back propagation method. Finally, weight and disease spread on the fruit are used to define fruit grading [16].

Table 3. Color features.

Color Space	Features
RGB	Non-uniform space, Device oriented, highly correlated
CMY	Complimentary color space, non-uniform
YcbCr	Linear and correlated, User-oriented, Human color perception
L*a*b	Non-Linear and correlated, Device oriented, Uniform space
HIS	Human color perception, User-oriented, Non-Linear and correlated
HSV	Human color perception, Artist oriented

Prabha and Kumar (2015) [17] offered a method for Image acquisition methods, such as digital image capture, before moving on to image pre-processing techniques, such as feature extraction. Three feature vectors are utilized to extract features: morphology, texture, and color. To extract image components for borders, morphology is employed. The texture characteristic describes a variety of visual patterns. In color feature extraction, RGB color space is transformed to HSI color space, and the extracting mean color intensity from calibration images using histogram, area, and perimeter. The area method and the mean color intensity method were improved, and their maturity detection accuracy was measured at 99.10% and 85.00%, respectively.

RGB color models, which are depended on the main colors red, green, and blue, are used to capture images (B). This color model splits an image into three planes: red, green, and blue, and calculates all color moments. (Kalsom et al., 2014) [18]. Table 3 illustrate various color space and their features. Laihang [19] offers a diagonal structure descriptor as a multi-feature representation approach. It's better at extracting intermediate features and allowing multi-feature fusion. The colour variations of diagonal pixels define five types of diagonal structure textons based on visual attention mechanisms.

ISSN 2063-5346

The mapping sub-graphs are then used to extract four types of visual characteristics, which are then combined into a 1-D vector. Numerous studies using three Corel data sets show that the suggested technique outperforms several state-of-the-art methods.

2.4.2 MORPHOLOGICAL FEATURES:

Morphological features, such as size and form are the most often-utilized parameters for fruit categorization. Size characteristics have physical dimensions that provide information about an object's appearance. Morphological characteristics include perimeter, area, main and minor axis lengths, and aspect ratio. Morphological characteristics are regularly utilized in businesses for automated sorting [20].

In comparison to the inherent irregularity in complex food, inspecting spherical and quasi-spherical item sizes of fruits are extremely simple. The predicted area, perimeter, length, breadth, main and minor axes are used to quantify the feature size. These qualities are often utilized in businesses for automated sorting. The area calculates the region's real number of pixels. Pixels of the region acquire the probable area. Feature extraction is based on the distance between two nearby pixels. The distance between the region's boundaries is measured in a perimeter (a scalar variable). The area and perimeter of every object, regardless of shape or orientation, are stable and efficient once segmented. Roundness, compactness, and aspect ratio are used to evaluate shape attributes. For evaluating fruit size, Kondo (2009) [21] has employed the maximum length, breadth, and diameter.

The shape of an agricultural product is unique or irregular. The shape is an important feature in fruit quality assessment and categorization. Length, width, convexity, compactness, roundness, elongation, length/width ratio, border encoding, Fourier descriptor, and invariant moments are the most often-utilized shape features in food quality analysis (Zhang et al., 2012)[22].

2.4.3 TEXTURE FEATURES:

Texture, as determined by a collection of pixels, indicates the surface appearance and distribution of elements and is helpful in machine vision applications that predict surface roughness, entropy, contrast, and direction, among other things.

Contrast, energy, correlation, and entropy are four characteristics used in qualitative analysis (Bagri and Johari, 2015)[23]. Structural texture, model-based texture, statistical texture, and transform-based texture are examples of texture features. Create a matrix based on pixel intensity values (grey- level co-occurrence matrix, grey-level pixel run-length matrix, and nearby grey-level dependence matrix).

Razak et al. (2012) [24] proposed an approach and algorithm that uses fuzzy digital image processing, statistical analysis, and content prediction to assess the quality of mango output. When compared to human expert sorting, this system is designed to create an appropriate algorithm for recognizing and categorizing the mango with more than 80.00 percent accuracy.

To categorize the Mozafati dates based on weight and various geometric parameters, Nozariand Mazlomzadeh (2013) [25] utilized an adaptive network fuzzy interference system as a decision-making approach. The weight, length, breadth, and the thickness of four date parameters are assessed using a fuzzy method, yielding a score of 93.50 percent.

Moallem et al. [26] the present grading system of an apple that uses a Multi-Layer Perceptron (MLP) neural network to segment defects. Using K Nearest Neighbor (KNN), Support Vector Machine (SVM), and MLP statistical, geometric, and textural characteristics are retrieved, and classifications are compared. For defective and healthy apples, the Support Vector Machine classifier achieves 89.20 percent and 92.50 percent accuracy, respectively.

Based on the quality ratio, Sahu and Potdar [27] present a system to detect maturity and defects in mango fruit. The fruit is spoiled if the ratio of quality value exceeds the threshold value. If the quality ratio value is less than the cut-off value, then the fruit is excellent. As a consequence, the recommended algorithm sort's mango fruits by quality, which is important for adding value to the fruit. Table 4 illustrates fruit quality investigation using various features implemented by various researcher.

Section A-Research paper
ISSN 2063-5346

Table 4. A comparison of various features for determining fruit quality.

Author	Fruits	Fruit Parameters	Fruit Features	Accuracy/
Wang et al.(2012)	Banana	Quality evaluation	RGB (Color)	Good result
Prabha (2013)	Banana	Evaluation of Maturity	RGB(Color)	99.10%
Pathare et al., (2013)		Quality, freshness	RGB (color measurement and analysis)	Good result
Kalsom et al., 2014	Mangoes	Size characteristics	RGB	Better result
Anand Jalal, Shiv Ram Dubey, (2012)	Apple	Quality evaluation	RGB, HIS (Morphological)	93%
Zhang and Wu.(2012)	pear	Physical properties	Length and width (Morphological)	88.20%
Zhang et al.(2012)	Banana, Grapes, Apple, Watermelon	Shape grading	Fourier descriptors (Morphological)	88.83%
Kondo(2009)	Pear	external quality grading	Depends on size Deformability, Roundness (Texture), and Complexity	Good result
Bagril and Johari, (2015)		Statistical, texture	GLCM (Texture)	Good result
Moallem et al. (2017)	Apple	Texture, Statistical, and geometric features	YcbCr Color space (Texture)	92.50%
Nozari et al. (2013a,b)	Date	Length, Width, Thickness	(Texture)	93.50%
Razak et al. (2012)	Apple, Mango	color, Size, and skin	(Texture)	80.00%
Sahu (2017)	Mango	Shape, size	(Texture)	Good result

2.5 CLASSIFICATIONS:

Computer vision has mostly been used to grade and determine the quality of fruits. It offers the potential to automate human grading procedures while also reducing repetitive inspection chores. Defect detection, categorization, and determining the maturity of fruits based on their appearance are all done with computer vision.

Fruit images may be characterized by a collection of features like color, texture, size, and shape using image processing techniques. These characteristics are utilized to create a training set, after which a classification algorithm is employed to extract the knowledge base that is required to make a judgment in an unknown instance.

In computer vision systems, a wide range of classification approaches, like fuzzy logic techniques (FL), artificial neural network techniques (ANN), histogram-based methods, support vector machines (SVM), histogram method, RGB color space method, and color mapping technique.

2.5.1 FUZZY LOGIC (FL) TECHNIQUE:

Economics, process control, operations research, management, and decision making, and most significantly for this study, pattern recognition and classification are all uses of fuzzy logic. FL is a type of language that is used to deal with opacity, and uncertainty. After the features have been stable, they are loaded into a classifier system, which generates an integer value or a quality index associated with the quality classification (real value).There are two ways to classify: traditional classification and classification based on computational intelligence. Statistical approaches, neural networks, and fuzzy systems are all part of the computational intelligence-based approach. Based on the idea of "partial truth", which refers to truth values that fall somewhere among "absolutely true" also "absolutely untrue." Uncertainty, human reasoning, and the perceptual process may all be described using fuzzy logic. Natural language is used to create fuzzy logic, and it is created using a set of rules to create an inference system, which is the foundation of fuzzy computing. Fuzzy set theory and fuzzy logic provide effective tools for expressing and interpreting human knowledge in the form of fuzzy IF-THEN rules. A new way of dealing with problems became a level of membership. A fuzzy set consists of items with varying degrees of membership. A set of fuzzy items contains items with varying degrees of membership.

A fuzzy set element might be a complete member (100percent- member) or a partial member (50percent-member) (between 0 percent and 100percent-member). That is, an element's member value is not prolonged limited to simply two values, it may be either 0 or 1.The membership function [28] is a mathematical function that determines the degree to which an element in a fuzzy collection is a member. There are several advantages to fuzzy logic. For starters, it is important and relevant to a wide range of systems; it is also simple to grasp and relatively adaptable; and, finally, it can represent nonlinear arbitrary-complexity functions. Fig. 5 depicts the overall design of the Fuzzy Inference System (FIS), which is an important concept in fuzzy logic. The fuzzy logic system (FLS) is a mechanism for mapping input data to output data that makes use of fuzzy logic ideas. Crisp integers are used to represent the system inputs, which are then converted into a fuzzy set using the Fuzzification function. If-then rules constitute the fuzzy rule base, and the fuzzy logic system rule base is a gathering of these fuzzy rules. Furthermore, the inference engine emulates human thinking by merging each output variable, combining all fuzzy subsets into a single fuzzy. Fig. 5 shows the fuzzy logic system architecture.

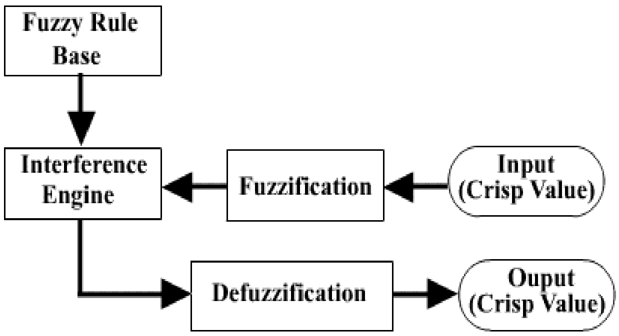

Fig. 5. A fuzzy logic system

The De-Fuzzification technique finally converts the fuzzy set of the interference engine into a crisp value. A fuzzy theory application is a fuzzy classification. In fuzzy classification, an occurrence might be associated with many classes, each with a distinct membership degree; traditionally, the addition of each instance's membership values must be homogeneous. The major benefit of fuzzy classification-based technique is that it may be used to analyze highly complicated processes [29].

As a decision-making tool, Ismail Kavdir et al. [30] utilized a fuzzy logic technique (FL) to evaluate apples. Different technology was used to measure quality criteria such as color, size, and flaws in apples. The FL system and a human expert developed for this purpose both rated the identical batch of apples. FL grading findings were found to be 89 percent in agreement with the human expert's results, indicating that the results may be tailored to suit the expert's expectations and grading criteria.

To assess the quality of local mango production in Perlis, Tajul Rosli et al. [31] developed and implemented image processing with digital fuzzy, statistical analysis, and content predicated analysis methodologies and algorithms. The study's primary contribution is the creation and implementation of an efficient algorithm for recognizing and sorting mangos with a grading accuracy of more than 80% when compared to skilled human sorting. This paper offers a mango sorting system based on fuzzy image processing for mango grade classification. The technique was created in the MATLAB programming language and may be used in a variety of fuzzy settings. The main benefit of this

Section A-Research paper
ISSN 2063-5346

technique is that it uses a fuzzy inference engine instead of relying on a human expert.

2.5.2 ARTIFICIAL NEURAL NETWORK (ANN):

The approach of artificial neural networks, which are used to define biological processes, has recently gained popularity. It has suitable decision-making power, which may also be utilized in the image investigation of biological products when no mathematical function can classify size and form [32]. It provides constant performance when paired with high-tech handling systems, in agricultural product classification, this is the most significant characteristic of these artificial classifiers [33]. These networks are based on the organic nervous system concept, and they have shown to be dependable in dealing with indeterminate data and circumstances requiring large-scale data interpolation. When specific input and output values are known, but the correlation between them is unclear or difficult to convert into a mathematical function, neural networks can help. In agricultural product grading, sorting, and identifying procedures, these situations are common. A multi-layered artificial network is seen in Fig. 6.

An artificial neural network is a collection of artificial neurons that are linked together. During the learning phase, ANN is a type of adaptive system that converts its structure based on the information that travels through the network, whether external or internal. Modern neural networks are statistical data, non-linear modelling techniques. They're frequently used to figure out how to solve intricate input-output connections or find data patterns.

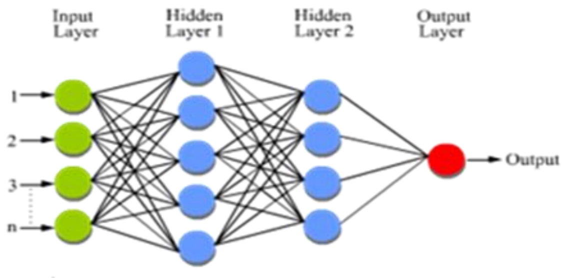

Fig. 6. Multi-Layered Artificial Neural Network

Smart agriculture with image processing, Monika Jhuria et al. [34] proposed fruit grading and disease detection with image processing. Artificial neural networks are utilized to build algorithms that can successfully identify and categorize the tested illness, with higher results for color and morphology (90%) in comparison to the texture. He furthermore devised a mango grading system based on weight, which he classified into five distinct classes using a mathematical formula.

Pujari et al. [35] developed an intelligent fruit sorting system by combining Artificial Neural Networks and Digital Image Processing. Apples are utilized in this project. Features are extracted using texture and color features. The addition of color features has considerably enhanced the system's performance. The effectiveness of categorization has increased up to 87.80%.

Brendon J et al. [36] introduced an image processing method and artificial neural network classification method, including a wavelet-based neural network classifier, for identifying the pest that damages apple fruits and leaves in orchards. The author was able to get a decent classification rate on a conventional neural network, which gives a 95-percent recognition rate, without making any changes in the learning process. Siti Sofiah et al. [37] used a Neural Network method to develop a basic color identification algorithm and used it in a system to assess the maturity of banana. The banana's recorded image is downsized, and the RGB color components are retrieved. The resized images color components are resized using a rudimentary heuristic method. To estimate the ripeness of the banana, for the rescaled image histogram is also gathered and a vector is utilized as a feature. They obtained a 96 percent accuracy for ripeness classification using a Neural Network classifier and an error back propagation model.

Section A-Research paper
ISSN 2063-5346

Hossain et al. [38] proposed method for determining the kind of fruit for labelling and weighing purposes, a fruit classification deep learning framework. The algorithm's first model is a network of six convolutional neural networks, while the algorithm's second model is a fine-tuned geometry learning model. To understand the performance of the proposed framework, a public dataset and a personal dataset are utilised, and it achieves 85 to 94 percent accuracy in non-clear image and clear complete image.Md. Ashiqul [39] presented a machine learning-based intelligent system that can identify papaya infections in his suggested study effort. SVC, random forest, k-means clustering, and CNN were utilised in this study, and among, CNN accuracy was good (98.4%).

2.5.3 K-NEAREST NEIGHBORS CLASSIFIER (KNN):

By comparing the input data to the training data, the input data is also identified using the K-Nearest Neighbors technique. It determines the distance between points in the input and training data using Euclidean distance measurements. Pragati Ninaws and others [40] New fruit recognition algorithms were proposed using a four-feature analysis method. A strategy based on shape, size, and color, as well as texture, to improve recognition accuracy. A total of 36 fruit images were collected for the fruit identification system. 20 fruit images are utilized for training purpose and 12 fruit images are utilized for testing purpose. They calculated the RGB component's mean value for feature extraction. The area, perimeter, roundness, and entropy values, as well as a form via threshold segmentation, can be calculated. When employing the KNN algorithm, the recognition result can be as accurate as 95%. Woo Chaw Seng et al. [41] suggested a novel fruit, identification approach that analyzes, categorizes, and recognizes a fruit image based on its color, size, and shape. As a classification algorithm, the KNN technique is employed, and it is a very good one. The pre-programmed fruit recognition system is accurately analyzes, classifies, and recognizes the fruit. In this study, Fruit was classified using a kNN classifier based on its mean RGB color value, area, perimeter, and shape roundness value, with a 90% accuracy rate.

Singh and Singh [42] used k-NN, logic regression, SVM, and linear discriminates classifiers to extract histograms of the oriented gradient, low texture energy, and Tamura features from good and defective apples using machine learning.

2.5.4 SUPPORT VECTOR MACHINE (SVM):

SVM is a type of supervised learning technique that may be applied to solve various categorization issues. The two classes were designed to handle classification issues, but by utilizing one-against-all or one-against-one approaches, they may be used to answer multi-class problems as well [43].

Support vector machines or networks are used in the machine learning for classification and analysis. They are made up of learning algorithms that evaluate data and find designs.

SVM training method builds a model that assigns new occurrences to one of two categories, making it a binary linear classifier that is non-probabilistic [44], in a set of given training examples, each one is labeled as relating to one of two groups. SVM's architecture is shown in Fig. 7. The SVM is a new pattern classifier that comprises a collection of generalized linear supervised classifiers that have been demonstrated to be more accurate than previous pattern classification techniques such as multilayer perceptual neural networks [45][46].Table 5 illustrates fruit quality investigation using various classification techniques implemented by various researcher.

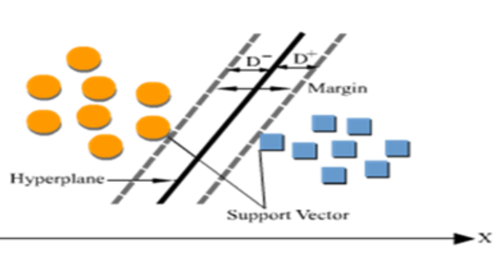

Fig. 7. Support Vector Machine (SVM's) an architecture

Section A-Research paper
ISSN 2063-5346

To accurately and fast categorize fruits, Yudong Zhang et al. [47] developed a multi-class kernel support vector machine-based classification method (kSVM). To eliminate the background of each image, a split and merge method was employed; second, size, texture, and color histogram properties of each fruit image were extracted to build a feature space, each fruit image's color histogram, texture, and form characteristics were extracted to create a feature; Third, to decrease the number of dimensions in feature, The PCA (Principal Component Analysis) method was employed. Lastly, three varieties of multiclass SVMs were developed: the Winner-Takes-All SVM, the Max-Wins SVM, and the Winner-Takes-All SVM, and Multi-Class SVM, SVM for Directed Acyclic Graphs, and SVM for Directed Acyclic Graphs. With an accuracy of 88.2%, the Max-Wins Voting SVM with the Gaussian-Radial basis kernel was the most accurate, according to the results.

Suresha M et al. [48] suggested an SVM Classifier-based effective automated apple grading system. There are 90 images in the database. The proposed technique effectivelydistinguishes between red and green apples. These RGB images of apples were converted to HSV images, and the fruit image was separated from the background using threshold-based segmentation. For apple categorization, apples average red and green color contains are computed. Using the linear kernel function for the SVM classifier, they claimed 100 % accuracy.

Bhargava et al [49] describes a method that distinguishes between four types of fruits and scores them based on their quality. The algorithm gets the images' red, green, and blue values first, then isolates the images' backgrounds using the split-and-merge approach. Color, statistical, textural, and geometrical elements are among the 30 attributes that are then retrieved. To distinguish different fruit varieties, only geometrical parameters (12 features) are used; additional elements are included in the fruit quality assessment. To determine the quality, four distinct classifiers are used: k-nearest neighbors (k-NN), support vector machine (SVM), sparse representative classifier (SRC), and artificial neural network (ANN). This approach, on the other hand, ignores the type of fault in the fruits and does not take into account the size of the fruit[50][51].

3. SORTING METHODS

Amruta[52] proposed technique for fruit grading system based on exterior factors such as ripeness, size, shape, and problems.Color, geometric, and shape-related characteristics were extracted using image processing methods. Pre-trained classifiers used these attributes to identify the fruit's maturity (unripe/mid-ripe/ripe), size (small/medium/large), and shape (well-formed/deformed).Behera et al [53] create an essay that uses machine learning and transfer learning techniques to categorise papaya fruits

The grading process is classifying fruits into various classes based on their size, shape, and color to maximize market value. Three general classes are recognized for the international market:
i) Premium Class
ii) Class-I
iii) Class-II

i) Premium Class:

The additional class is of higher quality, with the forms and colors of the variety and no inner flaws that might influence the intrinsic texture and flavor, as well as being disease-free. It should be free of any visible foreign matter; free from damage affected by pest/disease; free from malformation or irregular curvature of fingers; with pistils removed. Errors are permitted with 5% tolerance. It must be presented with care, taking into account the size and color consistency of the product, the condition of the product in the quality package, and the look of the packaging or pre-packing material.

ii) Class –I:

ISSN 2063-5346

Nearly identical to Premium Class in terms of quality, with the difference that a 10% tolerance is allowed with superficial defects not exceeding $2cm^2$ of the total surface area. Individual fruit can have minor form, color, and superficial skin defects that do not impact the overall look of the fruit's preserving characteristics. The size range in packaging can be broader, and the fruit does not necessarily need to be organized in the container.

Table 5. Different classification approaches for analyzing fruit quality.

Author	Fruit Input Images	Pre-Processing	Feature Extraction	Classifier	Accuracy/ Benefits
Ismail Kavdir 2003	Apple	resizing	GLCM	kNN	89%
Rosli et al. 2012	Mango	cropping		FL	80%
Monika Jhuria 2013	Mango	resizing	Color Morphology	ANN	90%
Pujari et al. 2014	Apple	Shade correction	Color and texture	ANN	87.80%
Bredon J. et al, 2010	Apple	Wavelet		CNN	95%
Siti Sofia et al., 2009	Banana	Resize	Color	CNN	96%
Hossain et al., 2018			Color	CNN	85-94%
Md Ashiqul et al., 2020	Papaya	scaling	Color	CNN	98.5%
Pragati Niwas et al., 2014	Apple, banana	RGB	Mean value	KNN	95%
Woo Chaw Seng, 2009	Various fruits	Color, shape	RGB color value	KNN	90%
Singh et al. 2019	Apple			KNN	87 %
Zhang Yudong et al., 2012	Pear	Split-merge background	Texture feature	KSVM	88.2%
Suresha M. et al., 2012.	Apple	HSI	Color	SVM	100%
M. Khojastehnazh et al., 2010	Lemon	resizing	HSI	RGB	94.04%
C. S. Nandi et al., 2012	Mango	RGB	Gaussian Mixture	RGB color	Response time 50 millisec.
Dah- Jye-Lee et al., 2011	Tomatoes, Date	RGB to HSI	Color	Color Mapping Tech.	Processing 60 dates per sec.
Mohd. Z.Abullah et al., 2002	Palm	color	HUI	HIS	80%
Esehaghbeygi et al., 2010	Saffron	Size, Color	Color features	SVM	90%
Shiv Ram Dubey et al. 2013	Apple	K means	Color features	K Means Clustering	Good result
Bhargava et al. 2020	Apple,Banana, Avocado, orange	Split-merge background	Color, statistical,texture,geometrical	SVM	95.72%
Lingeshwari et al. 2021	Tomato	Median filtering	RGB	K means clustering	Good result
Devi et al. 2020	Various fruits	resizing	GLCM	K means clustering	55 to 86 (PR)
Kishan et al. 2021	Tomato, vanilla	resizing	Color, statistical, texture, geometrical	CNN	95%

ISSN 2063-5346

iii) Class –II:

Such kinds of fruits may have some visible or inner flaws but are safe to eat while still fresh. With shape and color flaws that do not exceed 4 cm^2 of the total surface area. Local or short-distance markets are best served by this type. This category will meet the demands of clients who are not overly demanding and who value money over quality.

4. CONCLUSION

The application of image processing and computer vision technologies in the agriculture sector is focused on in this article. Shape, size, color, form, texture, and flaw are the utmost significant quality features of agricultural produce. To substitute labor-intensive fruit inspection, a computer vision system is used, which produces fair, non-destructive, and accurate results. Image acquisition, image segmentation, feature extraction, and classification are four key steps in computer vision-based feature analysis. The purpose of this investigation is to examine and evaluate the numerous approaches/algorithms suggested by researchers at various stages. While many researchers have provided many techniques for quality inspection of fruits, according to the findings of this study, a reliable computer vision-based system with enhanced performance is still necessary.

REFERENCES:

1. SeemaBanot, P.M. Mahajan, "A Fruit Detecting and Grading System Based on Image Processing-Review", *International Journal of Innovative Research in Electrical, Electronics, Instrumentation, and Control Engineering,* vol. 4, Issue1, 2016.
2. Anuja Bhargava, Atul Bansal. “Fruits and vegetables quality evaluation using computer vision: A review”, *Journal of King Saud University Computer and Information Sciences* 33243–257, 2021.
3. Gonzalez R. C. and Woods R. E., “*Digital Image Processing”*, Prentice-Hall, 2nd edition, 2002.
4. L Butz, C Hofmann, and B Tauscher. “Recent developments in noninvasive techniques for fresh fruit and vegetable internal quality analysis”, *Journal of Food Science*, 70(9): pp. 131– 141, 2005.
5. Anisha M Nayak, ManjeshR, Dhanusha, “Fruit Recognition using Image Processing”, *International Journal of Engineering Research & Technology (IJERT),* ISSN: 2278-0181, Volume 7, Issue 08, 2019.
6. Raja Sekar L, Ambika N, Divya V, “Fruit Classification System Using Computer Vision: A Review”, *International Journal of Trend in Research and Development*, Vol. 5(1), ISSN: 2394-9333, pp. 22-26, 2018.
7. George, Y.M., Bagoury, B.M., Zayed, H.H., Roushdy, M.I., 2013. “Automated cell nuclei segmentation for breast fine- needle aspiration cytology, *Signal Process,* 93(10), pp. 2804–2816, 2013.
8. Ghabousian, A., Shamsi, M., “Segmentation of apple color images utilizing fuzzy clustering algorithms Advances in Digital Multimedia”, pp. 59–63, 2012.
9. Jana, Susovan, Ranjan Parekh, and Bijan Sarkar. "Automatic Classification of Fruits and Vegetables: A Texture-Based Approach." In Algorithms in Machine Learning Paradigms, Springer, Singapore, pp. 71-89, 2020.
10. Devi, P.K., &Rathamani. Image Segmentation K-Means Clustering Algorithm for Fruit Disease Detection Image Processing. 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), 861-865, 2020.
11. Islam, M., Dinh, A., Wahid, K., Bhowmik, P. (2017, April). Detection of potato diseases using image segmentation and multiclass support vector machine. In 2017 IEEE 30th canadian conference on electrical and computer engineering (CCECE) (pp. 1-4). IEEE.
12. Dah-Jye Lee, “Rapid Color Grading for Fruit Quality Evaluation Using Direct Color Mapping”, IEEE Transactions on Automation Science and Engineering, vol. 8, No. 2, 2011.
13. Shiv Ram Dubey, Pushkar Dixit, Nishant Singh, and Jay Prakash Gupta., “Infected fruit part detection using K-means clustering segmentation technique”, *International Journal of Artificial Intelligence and interactive multimedia,* Vol. 2, pp.65-72, 2013.
14. Lingeswari, S., P. M. Gomathi, and S. PiramuKailasam. "A study of tomato fruit disease detection using RGB color thresholding and k-means clustering", *International Journal of Computer Science and mobile Computing,* Vol. 10, pp.51-59, Issue. 8, 2021.
15. Pathare, P. B., Opara, U. L., Al-Said, F.A., “Color measurement and analysis in fresh and processed foods: a review”. Food Bioprocess Technol. 6 (1), pp. 36–60, 2013.
16. Dubey, Shiv Ram and Anand Singh Jalal. “Detection and Classification of Apple Fruit Diseases Using Complete Local Binary Patterns.” *Third International Conference on Computer and Communication Technology*, pp. 346-351, 2012.
17. Surya Prabha D., Satheesh Kumar J. “Assessment of banana fruit maturity by image processing technique”, *J Food Sci Technol 52,* pp. 1316–1327, 2015.
18. Kalsom O., Yahaya M., MatJafri M.Z., Aziz A.A., Omar A.F., “Non-destructive quality evaluation of fruit by color based on RGB LEDs system”, *Int. Conf. Electron Des.*, pp. 230–233, 2014.
19. Khan MA, Lali MIU, Sharif M, Javed K, Aurangzeb K, Haider SI, Altamrah AS, Akram AT “An optimized method for segmentation and classification of apple diseases based on strong correlation and genetic algorithm based feature selection”. IEEE Access 7:46261–46277, (2019).
20. N. B. A. Mustafa, K. Arumugam, S. K. Ahmed, Z. A. M. Sharrif, “Classification of fruits using Probabilistic Neural Networks - Improvement using color features”, *TENCON 2011- IEEE Region 10 Conference,* pp. 264-269, 2011.
21. Kondo, N., “Robotization in fruit grading system”. *Sens. Instrum. Food Qual. Saf*. 3 (1), pp. 81–87, 2009.
22. Zhang, D., Spadaro, D., Garibaldi, A., Gullino, M.L., “Selection and evaluation of new antagonists for their efficiency against postharvest brown rot of peaches”. *Postharvest Biol. Technol*. 55 (3), pp. 174–181, 2010.
23. Bagri, N., Johari, P.K., “A comparative study on feature extraction using texture and shape for content-based image”, *Retrievalk. Int. J. Adv. Sci. Technol*. 80, pp. 41–52, 2015.
24. Razak, T.R.B., Othman, M.B., Bakar, M.N.B.A., Ahmad, K.A.B., Mansor, A.B., “Mango grading by using fuzzy image analysis”,

International conference on agricultural. Environ. Biol. Sci., pp. 18–22, 2012.

25. Nozari, V., Mazlomzadeh, M., "Date grading based on some physical properties". *J. Agric. Technol*. 9 (7), pp. 1703–1713, 2013.
26. Moallem, P., Serajoddin, A., Pourghassem, H., "Computer vision-based apple grading for golden delicious apples based on surface features". *Inf. Proc. Agric*., pp. 33–40, 2017.
27. D. Sahu, R. M. Potdar, Defect Identification and Maturity Detection of Mango Fruits Using Image Analysis, *American Journal of Artificial Intelligence*. Vol. 1, No. 1, pp. 5-14, 2017.
28. Dimatira, J.B.U., Dadiios, E.P., Culibrina, F., Magsumbol, J.A., Cruz, J.D., Sumage, K.,Tan, Gomez, M., "Application of Fuzzy Logic in recognition of tomato fruit maturity in smart farming" IEEE Region 10 Conference (TENCON), pp. 2031–2035, 2016.
29. Nedeljkovic, Igor. "Image classification based on fuzzy logic." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 34.30, pp. 3-7, 2004.
30. Ismail Kavdir, Daniel E. Guyer "Apple Grading Using Fuzzy Logic" *Turk J Agric* for 27 © T.BÜTAK, pp. 375-382, 2003.
31. Rosli B. Razak, Mahmod B. Othman, Mohd Nazari bin Abu Bakar, "Mango Grading By Using Fuzzy Image Analysis", *International Conference on Agricultural, Environment and Biological Sciences* (ICAEBS'2012), pp. 26-27, 2012.
32. Sa, I., Ge, Z., Dayoub, F., Upcroft, B., Perez, T., & McCool, "Deep fruits: A fruit detection system using deep neural networks", *Sensors*, *16*(8), pp. 1222, 2016.
33. Savakar, Dayanand. "Identification and classification of bulk fruits images using artificial neural networks." *International Journal of Engineering and Innovative Technology (IJEIT)* 1(3), pp. 35–40, 2012.
34. Monika Jhuria, Ashwani Kumar, and RushikeshBorse, "Image processing for Smart Farming: Detection of disease and Fruit Grading" *proceeding of the 2023 IEEE second international conference on image processing* (ICIIP-2013).
35. Pujari, J.D., Yakkundimath, R., Byadgi, A.S., "Recognition and classification of Produce affected by identically looking Powdery Mildew disease", *Acta Technol. Agric.* 17 (2), pp. 29–34, 2014.
36. Brendon J. Woodford, Nikola K. Kasabov and C. Howard Wearing, "Fruit Image Analysis using Wavelets", 2010.
37. Siti Sofiah, "Color Recognition Algorithm using a Neural Network Model in Determining the Ripeness of a Banana" *Proceedings of the International Conference on Man-Machine Systems* (ICoMMS) Batu Fer ringhi, Penang, MALAYSIA,pp.2B7-1- 2B7-4, 2009.
38. Hossain, M. Shamim, Muneer Al-Hammadi, and Ghulam Muhammad. "Automatic fruit classification using deep learning for industrial applications." IEEE Transactions on Industrial Informatics 15, no. 2 (2018): 1027-1034.
39. Islam, Md Ashiqul, et al. "Machine Learning based Image Classification of Papaya Disease Recognition." 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA). IEEE, 2020.
40. Pragati Ninawe, Mrs. Shikha Pandey, "A Completion on Fruit Recognition System Using K-Nearest Neighbors Algorithm" *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)* Vol. 3 Issue 7, pp.2352-2356, 2014.
41. Woo Chaw Seng, S. H. Mirisaee, "A new method for fruits recognition system", *Proceedings of the 2009 International Conference on Electrical Engineering and Informatics*, ICEEI 2009. 1. pp. 130 – 134, 2009.
42. Singh S, Singh NP "Machine learning based classification of good and rotten apple". Recent trends in Communication, Computing and Electronics, Springer, Singapore, vol 524.pp 377–386, 2019.
43. Zhang, Y.D., Wu, L.N., "Classification of fruits using computer vision and a multiclass support vector machine" *Sensors* 12 (9), pp. 12489–12505, 2012.
44. Website:http://en.wikipedia.org/wiki/Support-vector_ machine.
45. Kavdir I, Guyer DE, "Evaluation of different pattern recognition techniques for apple sorting". *Biosystems Engineering.* 99, pp. 211–219, 2008.
46. Yizhong Wang, Yanhua Cui, Shaohui Chen, Ping Zhang, Huafang Huang, "Study on fruit quality measurement and evaluation based on color Identification", *International Conference on Optical Instruments and Technology: Optoelectronic Imaging and Process Technology;* Vol. 7513, pp.75130F-1, 2009.
47. Yudong Zhang and Lenan Wu, "Classification of Fruits Using Computer Vision and a Multiclass Support Vector Machine", *Sensors* 2012, Vol. 12, pp. 12489-12505, 2012.
48. Suresha M Shilpa N.A Soumya B "Apples Grading Based on SVM Classifier International Journal of Computer Applications" (0975 – 8878) *On National Conference on Advanced Computing and Communications* - Ncacc, 2012.
49. Bhargava, Anuja, and Atul Bansal. "Automatic detection and grading of multiple fruits by machine learning." *Food Analytical Methods* Vol. 13.3, pp. 751-761. 2020.
50. Devi, P. Kanjana and Rathamani. "Image Segmentation K-Means Clustering Algorithm for Fruit Disease Detection Image Processing." *2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA)* p.p. 861-865, (2020).
51. Kishan Das Menon, H., Achal Raj Jain, M., Janardhan, V., & Deepa, D., "Digital grading and sorting of fruits". *Materials Today: Proceedings.43,Elsevier*, p.p . 3749-3756, 2020.
52. Supekar, Amruta Deepak and Madhuri S. Wakode. "Multi-Parameter Based Mango Grading Using Image Processing and Machine Learning Techniques" *INFOCOMP Journal of Computer Science 19,* p.p. 175-187, 2020.
53. Behera, S. K., Rath, A. K., &Sethy, P. K. "Maturity Status Classification of Papaya Fruits based on Machine Learning and Transfer Learning Approach".Information Processing in Agriculture, (ICECA-2020), IEEE, pp. 1353-1360, (2020).