



# Iot Based Real- Time Fruit Quality Monitoring And Grading System

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**Abstract:** The appearance of fruits plays a significant role in determining their quality. Not only does it affect their market price, but it also influences consumer choices and preferences. The visual appeal of fruits—such as their colour, texture, size, shape, and any imperfections—provides valuable insight into their overall quality. Traditionally, inspecting these aspects by hand is time-consuming and labour-intensive. To address this, the food industry has increasingly turned to computer vision systems for automating the inspection process of fruits and agricultural products. After years of development, these systems have proven to be a reliable and effective tool for ensuring high-quality standards. This paper provides an in-depth look at each step involved in this process. Grading systems based on the Internet of Things (IOT) are a creative way to automate and expedite the assessment process in commercial or educational contexts. With little assistance from humans, this system effectively grades and evaluates performance by utilizing Internet of Things components including sensors, microcontrollers, and cloud platforms. Using sophisticated algorithms, the system gathers data from the users or items being evaluated, processes it, and then offers real-time feedback and grading. Stakeholders can monitor and analyze results thanks to an intuitive interface, and cloud storage integration guarantees safe and convenient data management. By improving the grading process's effectiveness, precision, and transparency, this study hopes to provide a useful answer for contemporary industrial and educational applications.

**Index Terms** - IoT, grading system, sensors, microcontroller, cloud platform, automation, real-time feedback, data processing, smart evaluation, education technology, performance assessment, transparency, efficiency.

## I. INTRODUCTION

Customers place a great deal of importance on fruit quality, and suppliers are now required to supply fruits that satisfy strict quality requirements. In order to satisfy the inspection requirements of the fruit processing sector, fruit grading systems have been created recently. There are usually multiple procedures involved in handling fruits, such as sorting, grading, packing, transportation, and storing. Of them, grading is regarded as the most crucial phase in guaranteeing high standards of quality. Manual fruit grading has been done historically, which is costly and time-consuming. During busy times, labor shortages make this process even more difficult. The repetitious nature of manual inspection is also making it more difficult to recruit or train people to perform it. Robotic grading systems provide an accurate and affordable solution to these problems. External characteristics like size, color, shape, and surface appearance, as well as interior characteristics like sugar and acid levels, typically determine a fruit's quality. But when it comes to sorting and classifying fruits, size and color really matter most. In the fruit processing sector, these criteria are frequently utilized in conjunction with weight in modern fruit grading systems. In order to ensure quality control, computer-based machine vision and image processing techniques are essential. In recent years, fruit grading and evaluation have greatly improved due to technological advancements. Through the examination

of numerous physical attributes, these contemporary methods provide a more precise evaluation of fruit quality. Fruit size and form, for example, can be accurately measured by vision-based systems that are outfitted with CCD or CMOS sensors.

Software is also essential to this process; MATLAB is frequently used to create techniques for fruit classification based on color and size. Although color plays a significant role in sorting, it can occasionally be difficult to distinguish between fruits of similar hues. Size measures offer useful extra classification criteria in these situations.

Automated grading systems provide a dependable and effective solution for the fruit processing sector, guaranteeing constant quality. J. Ramprabhu et al. (2014) used the Gaussian Mixture Model (GMM), a pixel-wise classification method, to improve the process of classifying and evaluating fruit quality. This method allowed for the effective handling of substantial amounts of fruit while simultaneously enhancing the precision, consistency, and dependability of quantitative data. Edge extraction is a crucial component of size detection in this approach [1].

The study used the Canny method, one of the most effective edge-detection strategies, which employs a multi-stage algorithm to identify different edges in images, in order to accomplish exact edge recognition. In the meantime, Ali M. et al. (2011, 2012) presented a visual inspection technique for examining the lateral surface of cylindrical items, like pins, utilizing cameras and image processing. Their study proved how useful image-based analysis is for quality inspection across different industries[2,3].

In order to improve fruit detection and grading systems, Seema K. et al. (2016) investigated a variety of algorithms and classifiers, identifying four crucial strategies [4]. To increase classification accuracy, fuzzy logic makes use of digital fuzzy image processing, content-based predictions, and statistical analysis. Color and morphological analysis are improved by artificial neural networks (ANN), which improve detection outcomes. By comparing input data with previously trained samples, the K-nearest neighbors (KNN) classifier increases the recognition accuracy of fruit identification. Finally, by examining color changes at various ripening phases, color mapping evaluates the quality and maturity of fruit. All of these techniques work together to make fruit grading and classification more precise and effective.

A sorting and color grading method for citrus fruit classification based on the Gray-Level Co-occurrence Matrix (GLCM) parameter was proposed by Chandran K. et al. (2015) [5]. The degree of local variation in an image is measured by contrast, according to their findings. When the values of the pixels (i and j) are the same, there is little variation since the contrast is zero. Additionally, to increase the accuracy of fruit classification, GLCM simultaneously takes into account the relationship between a reference pixel and its neighbors[6].

A lemon sorting system that categorized lemons according to size and color was tested by Khojastehnazhand et al. (2010) in a related study. They used a specially designed instrument that was able to evaluate lemons in two stages: first, evaluating their internal quality, and then analyzing their external appearance. This method greatly increased the accuracy and efficiency of automated fruit processing, giving the sorting process greater reliability and effectiveness.

Nandi C. et al. (2014) [7] installed a CCD camera system on the conveyor belt in order to take pictures of the fruits. Fruits of various grades can be arranged using fuzzy rule-based algorithms. When two distinct maturity stages have nearly identical color patterns, misgradation may also take place. Yogitha et al. (2014) experimented with using distributed network architecture to connect a camera unit to a computer system via a GigE LAN environment in order to automate fruit inspection and grading [8]. Image processing, image capture, and decision-making are all part of the computer mission vision system employed in this study.

Agriculture can also benefit from a range of machine vision techniques [9, 10, 11]. These algorithms are commonly utilized due to their low cost and fast performance, Benefits and appropriate responsibilities for evaluation, measurement, and inspection. Fruit and vegetable detection, fruit size and weight estimation, fruit and vegetable identification, leaf area and yield estimation, plants, classification and grading, autonomous selective sprayers, and many other types of data are frequently collected from farms using computer vision algorithms[12].

## II. FRUIT GRADING SYSTEM

Fruits can be classified into distinct groups using image processing based on their size, shape, color, texture, bruising, stem, and calyx. Numerous items are graded. Vegetables include green paper, tomatoes, potatoes, carrots, oranges, peaches, and apples. This section discusses how many parameters are applied in a computerized fruit assessment system. F. Pla and F. Juste described fruit stems from profile pictures using a thinning-based method [13]. Protrusion skeletons are created using thinning techniques in the early stages of the thinning process. A modified thinning method may detect and identify fruit stems and other protrusions using digital signals. The stem or any projection from the fruit body must be located after it has been recognized for the purpose to provide this information to the destemming apparatus. Several fruit stem morphologies have been described using this technique.

San-Fuji apples are graded using five quality classifications based on neural networks [14]. Pixels are extracted from the image based on color and fed into the neural network as a source. Fruit images are graded based on the abundance and diversity of sick pixels, the red-to-other-color ratio, and the fruit's overall hue. With a worldwide categorization rate of 70%, accuracy approaches 95%.

In ZIn [15], V. Leemans divided apples into four different groups based on European criteria and evaluated two apple varieties: the crew Pleasant and Jonagold. The picture database contained over 1,000 fruit photographs (528 The golden Sweet and 642 Jonagold) divided into three approved classifications (Extra, I, and II), as well as a denial (each of which group accounting for 70, 20, and 30% of the collection measurement). The photographic grading process was divided into five phases: capture of images, background color categorizing, defect differentiation, sepal and stem recognition, problems characterization, and fruit categories based on excellence grade. The recommended method for measuring apple exterior quality yielded accuracy rates of up to 78% for Jonagold apples and 72% for Golden Delicious apples.

Near-infrared photos of the apple's calyx were taken, and an automatic system for identifying apple defects [16] was developed using Evolutionary Constructed (ECO) traits to distinguish blemishes and bruises from the stem end. The input Apple images are transformed iteratively to produce high-quality features. The accuracy rate for recognizing real apple blemishes and bruises was 94%.

A new method for grading Iyokan orange fruit was proposed by Naoshi Kondo based on a picture of the fruit. Among the various characteristics that were extracted were form, color, and roughness. The R.G. color variation, texture, and the feret's radius ratio were among the other metrics that were obtained. The weight of the fruit and all of its characteristics were fed into neural networks. Neural network output was assessed using the fruit's pH or sugar content reference value.

A novel technique for fruit form recognition utilizing the ideas of attractor and fractal dimension was presented in [17]. The use of neural networks for quantitative measurements and assessment of how uneven or regular the fruit's form is. The suggested approach for automated classification is more advanced and dependable.

In order to improve recognition accuracy, a novel fruit recognition method that integrates color, shape, and size was developed in [18]. Fruit photos are categorized and recognized using feature values derived from closest neighbors classification. Aidil Azwin, Zaipatimah Ali, Wong Bing Yit, Syed Khaleel Ahmed, and Nur Badariah Ahmad Mustafa Zainul Abidin and Zainul Abidin Md Sharrif demonstrated how to grade and sorting.

The application of fuzzy logic with support vector machines [19]. The agricultural produce is classified based on its size, shape, and grade. The obtained accuracy was superb. Hongshe Dang et al. proposed the Fruit Size Detection and Grading System algorithm [20]. An embedded grading system is used to put the algorithm into action. The algorithm has several advantages, including high grading accuracy, speed, and affordability. Coffee-Excelso Bean quality was rated in [21] using color, form, and size as parameters that allow us to assess the quality of green beans from a small sample.

In their [22] work, M. Khojastehnazhand et al. offered a revolutionary way for developing an identification mechanism that would grade lemons based on size and color. The color and volume of the fruit are determined during the calibration stage and then entered in an information system. In the grouping the platform, the computed color and volume are compared to the database's stored data. The fruit's ultimate grade was determined. The obtained accuracy rate was 94.09%.

The form characteristic can be efficiently obtained by first drawing the lines and then classifying the strawberry image using the the Kmeans method clustering approach, as proposed in [23]. The  $L^*a^*b^*$  color model is used to construct the suggested automated strawberry grading system.

The primary color approach on the stream is utilized to calculate  $y$ . The study found that berry size identification inaccuracy is less than 5.1%, color grading accuracy is 88.8%, and form classification is over 89%. It takes fewer than three seconds on average to evaluate one strawberry. Yousef Al Ohali [24] devised a computer vision-based technique for grading date fruits. The date fruit grading method extracts the following characteristics: flabbiness, size, shape, intensity, and defects. It classifies dates into three quality groups (grades 1, 2, and 3), which are chosen by specialists based on the retrieved attributes.

Dates with no faults, big in stature, a strong flavor, high flabby, and good form were labeled as of the best quality. S. Arivazhagan et al. developed a fruit detection system using color and texture [25]. This piece suggests the use of hues and textures together. Fruit can be evaluated based on texture, color, shape, and intensity. Fruit is classified using a minimal distance classifier based on Wavelet-transformed sub bands. Tajul Rosli described an automatic mango rating technique based on fuzzy image analysis in [26]. The proposed system evaluated mangoes based on their size, color, and skin properties.

### III. FRUIT CLASSIFICATION AND GRADING PROCESS

#### 3.1. IMAGE PROCESSING

##### 3.1.1. Basic Process Involved in Image Processing

As shown in Fig. 1, fruit detection and grading by a five-stage image processing technique [27].

Stage 1: In an image-processing sequence, first a clear digital photography of the fruit is taken through a camera and stored in the digital platform from where the photographs can be viewed and processed accordingly.

Step 2: The pre-processing stage involves image enhancement for better quality. Smoothing reduces roughness, and any unwanted noise is removed while the size is adjusted for consistency. In addition, contrast is slightly enhanced, and RGB images are converted to greyscale to make further analysis easier.

Stage 3: Image segmentation is the process of dividing an image into distinct sections to make it easier to analyze. This step helps isolate important areas, such as specific features of the fruit, allowing for more accurate processing and identification.

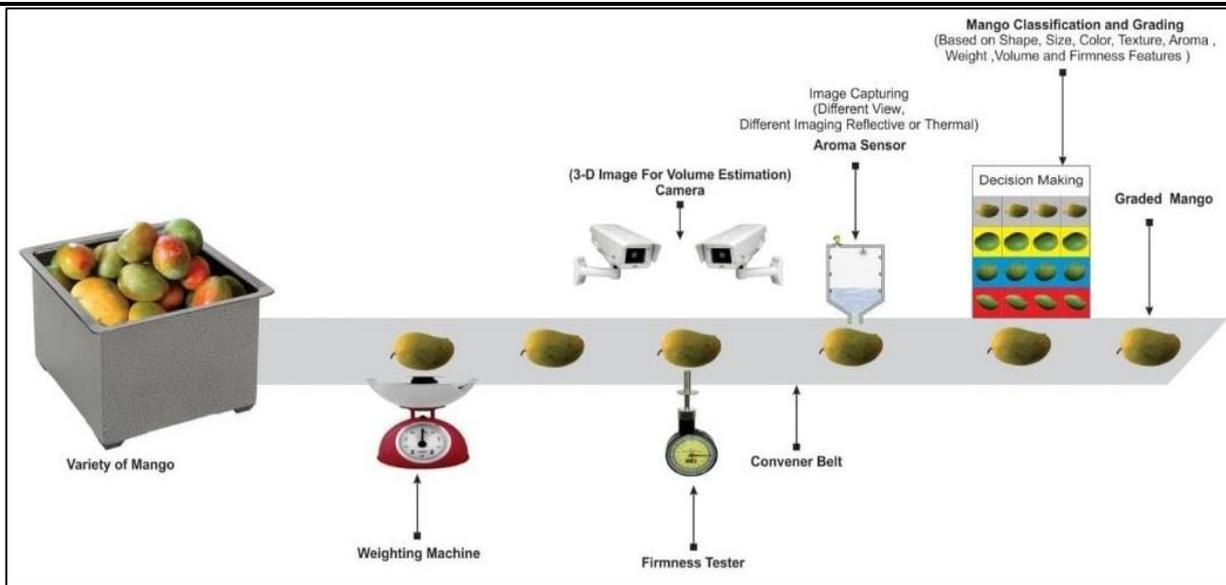
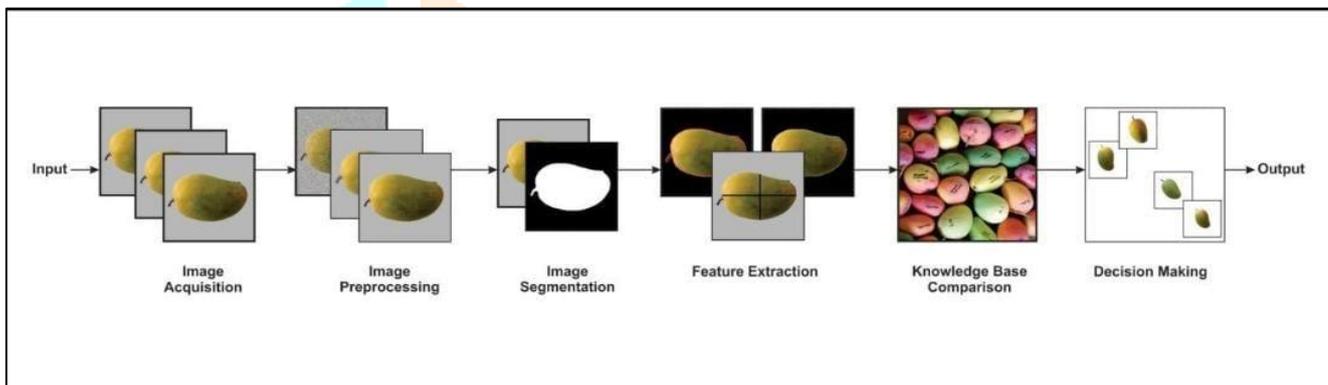


Fig 1. Model for fruit separation



Step 4: Feature extraction involves identifying the major characteristic of the image, such as color, texture, and shape. This will simplify the data because there's a focus on the most relevant details only, making the classification process more efficient and cutting down the resources needed for analysis.

Stage 5: In the categorization stage, the numerical characteristics of the image are analyzed and classified based on specific attributes. A neural network is then used to train the system, which will then be able to accurately identify and categorize different fruit diseases.

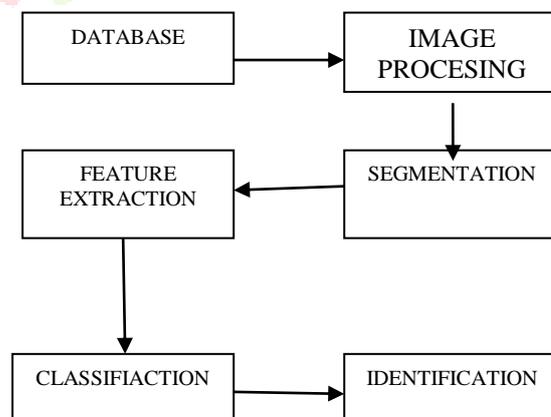


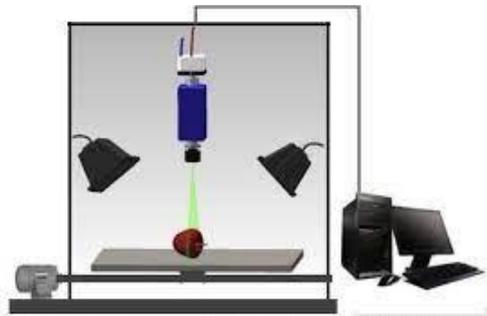
FIG 2. Grading process of fruits and vegetables

### 3.1.2. Image Acquisition

Lighting systems utilized in fruit research are carefully designed to enhance image analysis (this includes both front and back illumination). Parameters related to surface quality, such as color, texture and skin imperfections, are assessed through front lighting. However, illumination also plays a crucial role in analyzing size and shape by emphasizing border elements. Various imaging techniques—such as conventional, hyperspectral and multispectral—have been effectively implemented to evaluate the quality of agricultural products (see reference [27]).

### 3.1.3. Image Preprocessing

Crop studies often do not use common front and back lighting, but rather specific lighting systems. Front lighting captures outer quality attributes such as hue, texture, and epidermis defects, but uses backlighting for measuring the size and shape of border elements. Different imaging technologies, including standard, hyperspectral, and multispectral approaches, have been applied to the imaging of agricultural products with success; however, the analysis of agricultural product quality is still a challenging task [27].



**Fig 3. Image acquisition**

#### 3.1.3.1. Colour space transformation

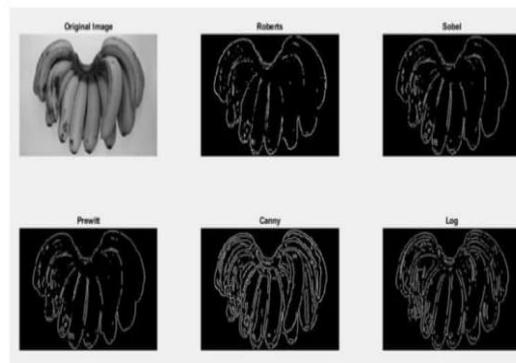
Most of the CST-based applications use the HSI color space. Here, saturation describes the texture of the image and is used in the generation of a monochrome version. A simple noise reduction filter is used to improve image quality, whereas both a modified unsharp mask filter and a median filter reduce peak noise to allow for more accurate analysis. [28].

#### 3.1.3.2. RGB

Most of the Computerized Sorting Technology (CST) uses Hue, Saturation, and Intensity (HSI) color space where saturation assists in forming a monochrome image and gives an image of its texture. Noise reduction filter is used to decrease the noise of the image; in addition, a median filter and modified unsharp filter is applied for peak noise removal and further sharpness of the image. [28].

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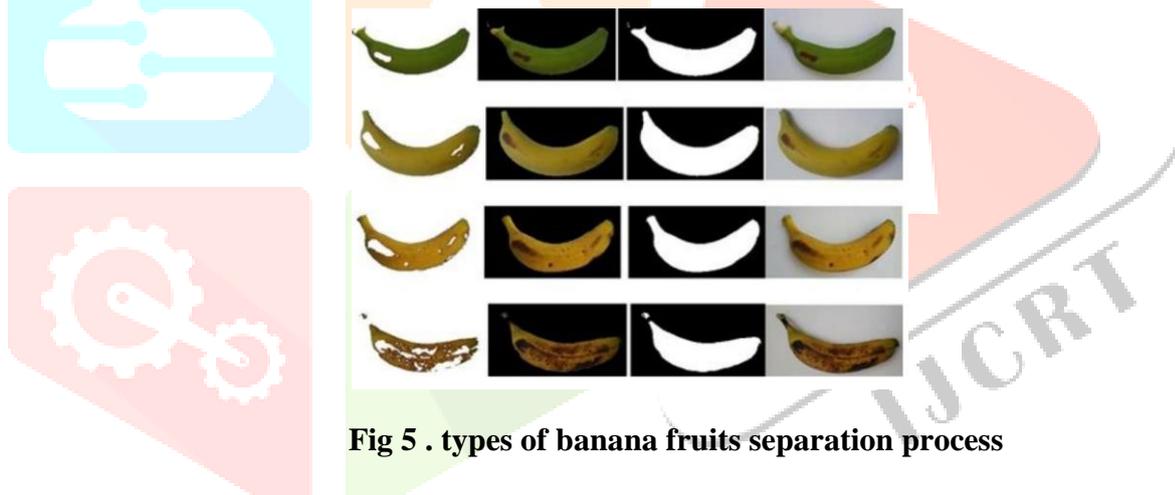


**Fig 4. Image pre processing**

### 3.2. SEGMENTATION

Segmentation of pictures is the procedure of dividing an electronic image through smaller components or segments. Ghabousian et al., [29] presented a fuzzy categorization technique to improve accurate segmentation in apple color photos. This approach use the  $L^*a^*b$  color space, which is very useful for separating apple-colored images.

For example, Figure 5 shows the segmentation process for banana fruit types with brown spots removed. The sequence includes: i) the original input image in the first column, ii) the segmentation mask in the second column, iii) the segmented fruit in the third column, and iv) the fruit with brown spots removed in the fourth column.



**Fig 5 . types of banana fruits separation process**

Before applying a vision-based approach to improve images, a segmentation step using the Hough transform was performed. The Naive Bayes classifier was then used to categorize images of fruits and vegetables. To automate the image segmentation process, a texture-based method was proposed [30].

To train the classifier for optimal results, images were captured from all 360-degree angles. The classifier's feature vector consists of matrix-based features from the grayscale image and its fractal dimension. Among various techniques, Kanjana's E-K-Means Clustering method [31] proved to be more effective. For comparison, the Existing-KMeans neighbor method achieved results ranging from 49.6 to 77.5, the Support Vector Machine algorithm ranged from 40.6 to 66.9, and the E-K-Means clustering algorithm produced results from 52 to 36.

Dah-Jye-Lee et al. [32] employed spectrum connecting to study the features and ripening stages associated with agricultural merchandise such as date fruits and tomatoes. Similarly, Jay Prakash Gupta et al. [33] employed K-means unsupervised clustering to create an entirely novel approach for color-based fault localization in fruits. K-means is a typical technique used to identify meaningful pixel pairings in graphics.

### 3.3. FEATURE REPRESENTATION

Feature extraction is a key step in image processing, with the goal of identifying the most "interesting" aspects of an image. These characteristics, often referred to as descriptors in pattern recognition, help define the unique features of the image. An effective feature detector is defined by its repeatability—its ability to consistently identify the same features under different conditions.

In the case of fruit photos, the following step after classification is to find the features that perfectly represent the fruit. Color, shape, size, and texture are all common qualities. For object detection and classification, several visual descriptors and local feature detectors are used. Popular strategies include the Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), and Speeded Up Robust Features (SURF), which will be discussed further in the following section.

#### 3.3.1. Feature extraction techniques:

The primary apparent features that define fruit, such as its color, dimensions, shape, and texture, are critical for precise assessment after classification. A feature descriptor represents the image or its parts by extracting essential information while removing irrelevant details.

#### 3.3.2. Colour attribute analysis

Color is one of the most visually striking aspects of any image and plays a vital role in classifying, rating, and distinguishing healthy fruits from defective ones. Various methods compare the color of a fruit to predefined reference colors to determine its maturity. Different color models, such as HIS, HSV, JPG, Lab\*, GALDA, RGB, and sRGB, are commonly used in these techniques. For more detailed information about these color models, references [34,35] offer in-depth descriptions.

Research has explored numerous methods for analyzing fruit characteristics, and a detailed overview of color feature extraction can be found in [36]. According to [37], back projection techniques are applied after 2D color histograms are used to estimate co-occurrence frequency, helping to assess the maturity and quality of date fruits. In [38], an in-depth analysis of feature extraction strategies, color models, and segmentation algorithms for fruit disease detection and grading is provided. Additionally, [39] highlights the use of the Gaussian Mixture Model and Fuzzy Logic to develop a mango sorting system based on size and maturity, achieving an accuracy rate of 88% to 92% across various maturity levels.

#### 3.3.3. Size feature extraction

The size of a fruit is a significant factor in determining its quality, with larger fruits generally considered superior and more valuable. However, measuring the size of fruit can be tricky due to its inherent inconsistencies. Common techniques for estimating fruit size include calculating the area, perimeter, weight, height (or length), width, and volume. These methods provide valuable insights into the overall size of the fruit, which is often a key indicator of quality. To give a more thorough study, other size characteristics such as the major and minor axes, radius, and equatorial diameter are also used.

Diameter inspection is vital in determining the superiority of fruits. This topic is thoroughly discussed in [40]. [41] provides a comprehensive assessment of non-destructive methods for measuring the size of fruits and vegetables. Weight, volume, analytical, asymmetrical, and statistical approaches to size measurement are briefly discussed in [42]. [43] discusses methods for the automatic evaluation and quality assessment of fruits and vegetables, with a focus on size and volume estimation. In [44], a classification approach for date fruits is provided that uses shape and size features paired with texture descriptors, where shape and size are determined by fitting an object to an ellipse. Mangoes are also graded non-destructively according to ripeness and size (area). [45], using thermal imaging with a FLIR One camera.

### 3.3.4. Shape feature extraction

Shape is a key factor in fruit selection, classification, and grading. As highlighted in [46], combining multiple parameters like color, structure, and dimension has greatly improved the identification of strawberry cultivars and their quality assessment. By using a combination of features, classification accuracy improved to 67.9%, than using just a single feature. In [47], date fruit classification was enhanced by considering shape, size, and texture. Advanced techniques like Local digital Pattern (LDP) and Weber Local Descriptor (WLD) histograms, along with Fisher Discrimination Ratio (FDR)-based feature selection, achieved an impressive 98% accuracy in identifying and categorizing date fruits.

## IV. VARIOUS TECHNIQUES AND FRUIT GRADING METHODS :

### 4.1 Design And Development Of Onion Grading Machine

Research is being conducted on an onion grading machine designed to sort onions based on their size. The machine consists of a feeding hopper, an iron circle, a supporting frame, and a grading cylinder made of PVC tubes with a 20 mm diameter. The hopper's front section is adjustable for different onion sizes. The grading cylinder has four exits, split into two sections. The first section is longer and has two exits: one for separating smaller onions (less than 4 cm in diameter), and another for medium-sized onions (4 to 6 cm). The second section is shorter, with an exit for larger onions (over 6 cm).

The machine uses soft wire mesh and rubber-wrapped PVC tubes at the exits, which help cushion the onions and minimize damage during sorting. For mechanical operation, an electric motor can be connected via a pulley and belt system. Alternatively, a lever or handle can be used for manual operation. The grading cylinder can rotate at speeds of 10, 15, and 20 rpm and can be tilted at angles of 2°, 3°, or 4° against the horizontal axis. The best performance is achieved with a rotational speed of 14 rpm and an angle of 4° against the plane axis. The maximum sorting efficiency, sorting onions into three grades, occurs at this combination of speed and tilt.

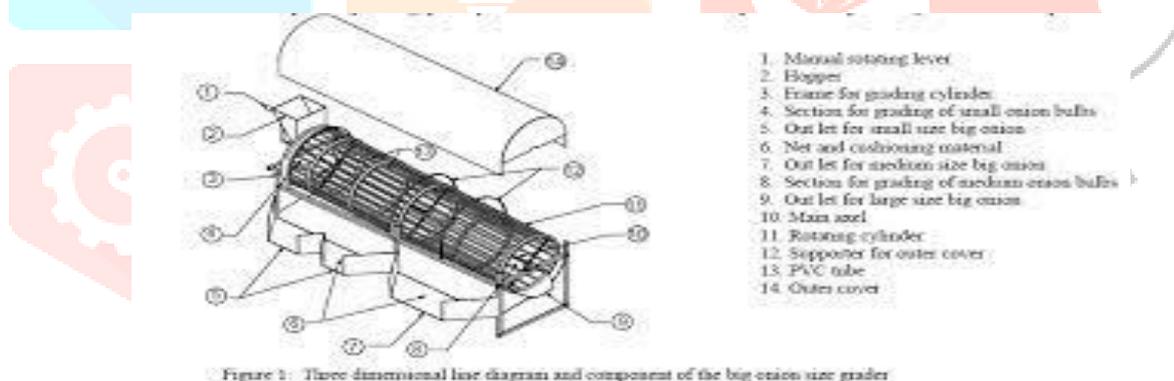


Figure 1: Three dimensional line diagram and component of the big onion size grader

### Fig 6. Grading machine

The grading cylinder achieves its maximum efficiency when set at a 3° inclined angle and a speed of around 15 rpm. However, the optimal grading efficiency for sorting into three grades is actually achieved at 14.45 rpm and a 2.99° inclination angle. When operating at this ideal efficiency, the grader has a maximum capacity of 630 kg per hour, with grading efficiencies for minimum, medium, and maximum onions reaching 84.48%, 92.96%, and 90.24%, respectively (Aniket V. Joshi, 2016)

### 4.2 Orange Sorting Machine: [49]

This review focuses on grading oranges, using color images of the fruit as input for the system. It's been observed that various factors—such as the camera's settings, distance from the subject, background, and the light source and its intensity—can affect the appearance of the same fruit in photos. To ensure consistency in the images, an imaging chamber is designed to keep each fruit sample uniform. The chamber is a cylindrical plastic box painted white, with white paper applied to the base to reduce reflections. The interior of the box is lined with light-reflective material, and LEDs are installed at the top to provide internal lighting. The light intensity inside the box is measured at 430 Lux using a digital Lux meter. A UPS power source is used to avoid voltage fluctuations, ensuring stable lighting conditions that meet the diffused daylight standard set by Hunter Labs.

The camera used for capturing images is a Sony DSC 2000 in VGA mode (640 x 480), with the flash turned off, the light set to auto mode, and the image angle set to 0°. For each shot, the fruit is positioned 18 cm away from the camera (Aniket V. Joshi, Prof. N. P. Awate, 2016).

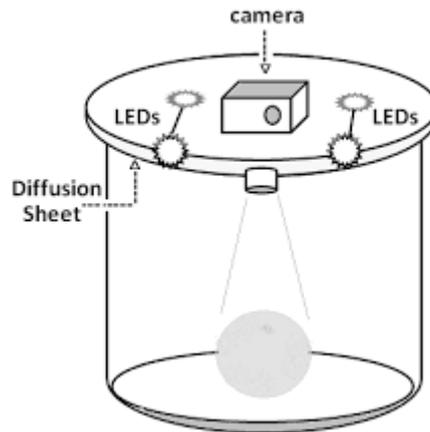


Fig . 7

### 4.3 Lemon Grading System:

This approach uses image processing to sort lemons. When a picture of a lemon is taken, the system compares the size of the captured image with a standard reference image to grade the fruit based on its dimensions. To make this comparison, the background of the image is removed. The image is then divided into different regions to estimate the lemon's volume. While the fruit moves past cameras during sorting, photos are taken, and the color and volume of each lemon are analyzed using HSI color values.

The sorting process involves comparing the collected data against a database to determine the fruit's grade. Fruit that meets both the volume and color thresholds established during a calibration stage is classified as "Class One." If the color is below the threshold but the volume exceeds it, the fruit is classified as "Class Two." If the volume is below the threshold, it is categorized as "Class Three."

At the end of the process, the center of gravity of the fruit is identified, which is then used for automated sorting based on the fruit's characteristics. To accurately convert the pixel count of the fruit in the image to its actual volume, the system scales the foreground (fruit) pixel count. The real and measured volume of an ideal sphere are used to find a scaling factor,  $C$ , which is  $2.35 \times 10^{-4}$ . This scaling factor is applied to convert the pixel measurements into cubic centimeters ( $\text{cm}^3$ ). (Aniket V. Joshi, Prof. N.P. Awate, 2016).

### 4.4 Physical Properties For Lemon Fruit : [51]

To separate and classify lemon fruits effectively, it's important to study their physical characteristics. This helps prevent damage from impact with metal surfaces and allows for a precise determination of size differences between fruits. For this study, two types of lemons—seedless Lisbon and frost Eureka—were chosen. While these varieties differ in terms of interior quality, they appear quite similar on the outside.

To analyze the physical properties, measurements were taken along three axes: major, intermediate, and minor. Additionally, the projected area (PA) was calculated from camera images taken under controlled lighting conditions. The images were then processed using ImageJ version 1.46d software on a computer. From these processed images, several key physical attributes, including mass, volume, and diameter, were computed. A table was created to list these characteristics for comparison and further analysis.

Table 1 : Physical Properties

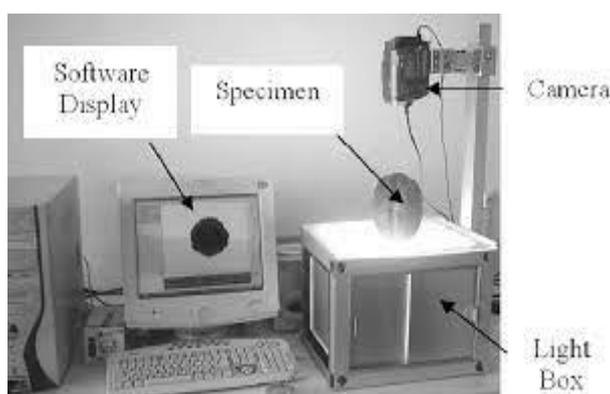
Property	Seedless Lisbon		Frost eureka	
	High	Low	High	Low
higher dim(mm)	62.84 5	49.3 1	70.18 1	58.4 5
Intermediate dim.(mm)	57.41	43.3 2	59.27	46.3 6
lower dim.(mm)	55.31	42.6 1	58.33	45.5 3
Geometric mean dia .(mm)	58.46	45.3 1	62.14	49.8 3
Mass(g)	106.6 1	48.9 6	122.2 7	62.2 3
Actual volume (cm <sup>3</sup> )	106.4 2	48.6 4	126.3 3	63.3 6

#### 4.5 Physical Properties of Orange:[52]

The mass, volume, and specific gravity of oranges are essential physical characteristics when it comes to sizing them. The sizing system measures parameters like weight, surface area, height, width, and length. To examine these characteristics, three different size categories were chosen: small, medium, and large, with fifty samples taken from each size.

To determine the physical properties of the oranges, an image processing technique is used. The system includes a light-generating chamber that emits light from behind the fruit. The equipment setup consists of three main components: a camera stand, a diffuser, and a light source. The light source is designed to illuminate the lower part of the diffuser, which then spreads the light evenly.

The camera captures the image, and the picture is sent to a capture card that converts it from analog to digital. Once the image is digitized, it is transferred to the computer's image processing software. Through the software's display window, we can analyze the fruit's dimensions using three different orthogonal views (pictures taken from three angles). This allows for a precise understanding of the fruit's size and shape. (Aniket V. Joshi, Prof. N.P. Awate, 2016).



**Fig 8. Image processing technique**

## V. MACHINE LEARNING TECHNIQUES

Syntactical and statistical classifiers are used to group fruits into quality categories. Several classifiers include:

### 5.1.Linear Discriminant Classifier(LDC)

The linear geometry Discrimination classification (LDC) is an statistical approach for determining an imaginary linear the line that breaks up contents into different categories, assuming that the info can be detached linearly [53]. The above method has been applied when categorizing date fruits [54]. Initially, the information's original characteristics are combined in an ordered manner to generate additional characteristics. The fresh characteristics are then used to group the data into the right classifications.

Bernard Gosselin and Devrim Unay used an LDC test to classify apples [55]. The goal is for reducing the requirement works in order to obtain a decision boundary with linearity that breaks up the domain of features into two separate categories. For deciding the group that the fruit relates to, the Euclidean distance is used for calculating the separation between the test fruit's characteristic values and the stored samples used for training. The K-Nearest Neighbors (KNN) algorithm then decides on the 'K' closest examples to the requested fruit. For the Fruit The recognition System, 'K' is set to one, which suggests that the provide information fruit is designated contingent on the learning of the most adjacent fruit example. The fruit is put into the group of objects that the next closest one belongs to.

### 5.2.Support Vector Machines (SVM)

Support Vector Machine (SVM) is a powerful machine learning method that has performed exceptionally on many different types of category tasks[56]. It is an elastic strategy for recognizing nonlinear and linear in data[57]. SVM works by first mapping the information into a space with multiple dimensions with kernel functions, allowing it to handle intricate information patterns. Once in this higher-dimensional space, SVM seeks the optimal expressed a hyperplane that breaks down the data by the greatest possible margin.

Originally, SVM had been designed for binary (two-class) tasks such as classification. However, for multi-class issues and to it can be mushroomed with approaches such as "one-vs-one" or "one-vs-all." [58]SVM has been used in a variety of procedures for making decisions, including detecting weeds in fields of wheat [59]. In this context, SVM aids when choosing whether particular regions should be administered, increasing the effectiveness and accuracy of the weed control process.

### 5.3.Nearest Neighbor Classifier(k-NN)

K-Nearest Neighbors (K-NN) is a statistically classification approach that looks at the subject matter based on geographical in nature the units of measurement. Parallel or accessibility. It decides numbers based on the most common organizations among its 'k' nearest neighbors[60]. In the Fruit Knowledge Although it as a whole, K-NN was used as a classification algorithm to identify fruits based on multiple parameters such as mean shade quantities, a roundness, subject matter, and limits. In 2013, Woo Chaw Seng and Seyed Hadi Mirisae [61] published a study in the \*International Journal of Computer Applications\* that looked into this approach.

In their computer system, produce perimeter as well as area are used to represent the fruit's their dimension. These magnitude elements determine one type of fruit from yet another. After typing the initial conditioning data, the system is primed for labeling new fruit samples. The system works in two stages: the first is an offline process in which it trains using information about cells that need to be sprayed versus those that do not and computes a decision function. Another advantage stage is a computerized system that makes decisions for new incoming samples using a pre-calculated decision-making function.

In another investigation, LS-SVM [62] (Least Squares Support Vector Machine) was used for automatically determining the quantity of darkening on mango fruits. Unlike conventional SVM, LS-SVM resolves linear algebraic rather than rectangular difficulties with programming. The LS-SVM classifier relies heavily on kernel function chosen and optimal kernel elements. As a result, the Radial Basis Function (RBF) kernel was chosen for its rapidity and effectiveness during the procedure for training.

## 5.4. Artificial Neural Network (ANN)

Artificial neural networks (ANNs) can be considered as a derivative of various categorization techniques, encouraged by the way nerve cells in humans function[63]. These networks are proving to be very successful at handling difficult data and solving problems that necessitate interfering with enormous amounts of information. Kazuhiro Nakano[64] used an ANN to evaluate the shade of apples, which is a prime example of a neural networks implementation. In the present instance, the first artificial neural network connection (A) was used for determining whether the apple's outermost shade was normal or unusually red. Kavdir and Guyer used computer-generated neural networks to distinguish between Empire and Golden Delicious apples based on their outward appearance (65). A different application possibility for neural networks is determining the sugar and acid quantity in iyokan oranges. In the current research, the network consisted of one output node identified as and four input nodes, which were separated by an unnoticed layer. The participation data, comprised of four categories, was used to classify the production data into five classifications. The system was trained on 25 iyokan oranges, with the remaining five used for testing, and the Kalman filter learning approach was applied for training[66].

T. Morimoto, T. Takeuchi, H. Miyata, and Y. Hashimoto also identified a neural network techniques for evaluating the determine of fruit[67]. They used a single-dimensional profile data, formed of radii between the fruit's centroid and various measurement points along the profile. To train the network, the error forward propagation learning strategy was utilized, enabling the system to detect and assessment the fruit's determine accurately.

## VI. METHODOLOGY

We conducted our research using four different information sets, each corresponding to three types of fruit: oranges, plums, and gala apples. Two datasets were for oranges, while the extra two were for plums and gala apples. Table I contains specific details about each dataset. The primary machines consists of a conveyor belt with independent fruit cup holders that rotate the fruit on a single axis to display its entire surface for imaging. The computer vision system is mounted above the conveyor belt and includes appropriate lighting and multiple cameras to capture both visible and infrared spectra (see Fig. 1). These cameras sync to capture pictures that turn of the fruit.

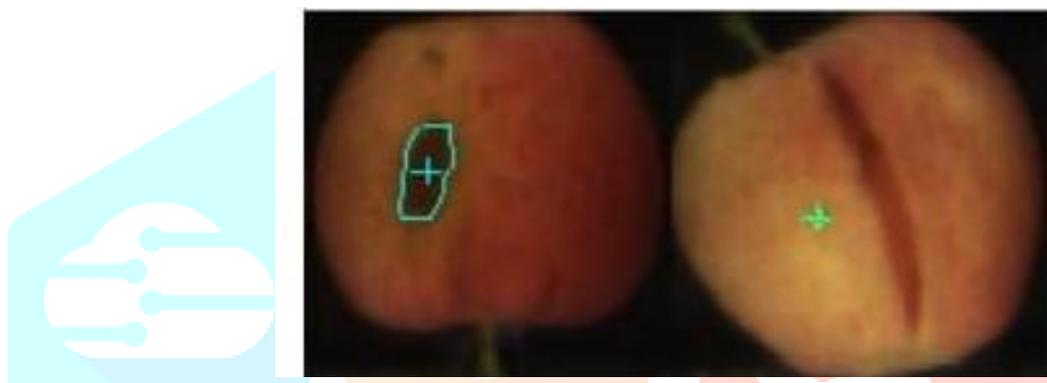
Figures 9 show what is apparent and infrared spectrum of the fruit. To accurately reflect the training and test datasets, every set of data was selected at random into two parts [68]. Following best practices, the splits were stratified to ensure that each class had an equal proportion of samples. The computer vision device had been adjusted for each fruit broadening based on images from the education and training dataset. This involved manually selecting pixels that represented key colors for color separation, allowing for separation of the foreground from the regions that are demonstrating the condition of the fruit (Fig. 9). The software then categorized the remaining images using similarity measurement metrics.

Next, we identified additional locations with potential (ROI) within the classified fruit show areas, which we named "fragments." Depending on the fruit categorization, these blobs may reflect natural sources external characteristics such as stems or calyxes, as well as a number of different flaws. To identify these ROI, we manually selected images that best constituted the blobs' elements and typical fruit surface areas. The software then classified the remaining pixels based on comparison parameters. Next, we realized more places that were interesting (ROI) within the categorized fruit appear areas, which we designated "fragments." These blobs can reflect organic surface characteristics, such as stems or calyxes, depending on the fruit classification, and can also indicate numerous types of flaws. To identify these ROI, we manually selected images that best constituted the blobs' elements and typical fruit surface areas. The software then classified the remaining pixels based on comparison parameters.



**Fig. 9 Visible spectrum.**

To produce the primary colors that would be used as input characteristics for the blob classification algorithms, we finally categorized the blob ROI using the same differentiation technique as in the previous steps (Fig. 9). Figure 9: A Gala apple with a flaw is shown in both the visible and infrared spectrums. An illustration of how to choose the predominant fruit colors by hand portion of the belt conveyor to accomplish segmentation (c). Finding the imperfection area in the segmented image (d) and manually identifying the prominent colors that correspond to it (e) are the next steps.



**Fig 10. Image processing**

Figure 10: Blob categorization example with the trained AdaBoost. Gala apples with flaws are classified by the ECC. Types of blemishes are classified as (a) severe and (b) minor. Each blob class had 10–20 blob examples chosen. For every fruit variety, we trained blob classifiers using AdaBoost.ECC, setting the ensemble size to 150.

In our research, we worked with four different datasets, each featuring three types of fruit: oranges, plums, and gala apples. Two of these datasets focused on oranges, while the other two covered plums and gala apples. Table I provides a detailed breakdown of each dataset.

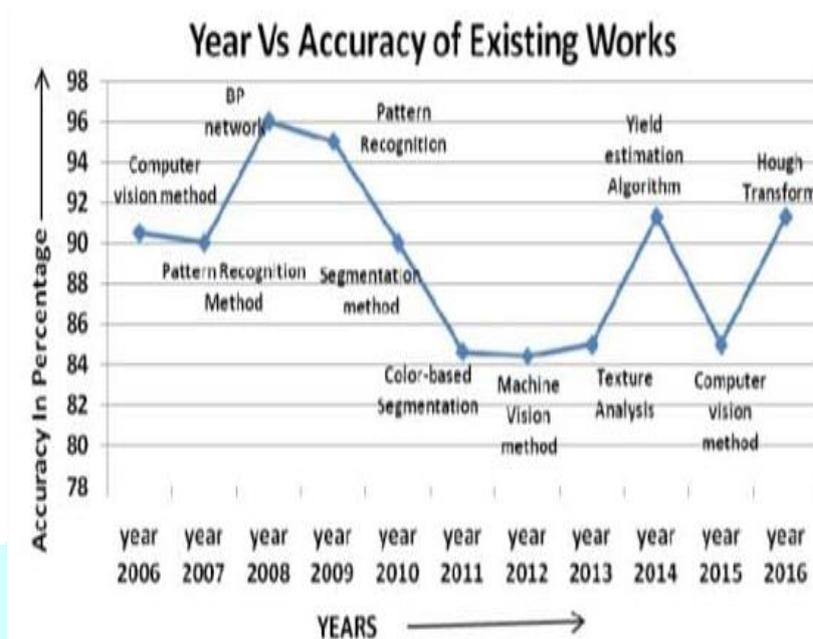
To capture excellent pictures, we used a conveyor belt system with specialized fruit holders for drinks. They are the holders rotate each fruit on an identical direction, making the entire surface visible for imaging. Positioned above the conveyor belt, our computer vision setup includes multiple cameras and dedicated lighting, allowing us to capture images in both visible and infrared spectra (as illustrated in Fig). The cameras work in sync to capture images as the fruit rotates, ensuring a comprehensive view of each sample. Fig. 2a-b shows how the fruit appears in both visible and infrared spectra.

To generate the training period and test datasets, each dataset was randomly split into two parts. To maintain balance, we used a stratified approach, making sure each fruit type was evenly represented in both sets. Before running the classification, the computer vision system was carefully calibrated for each fruit variety using images from the training set. This process involved manually selecting key pixels that represented distinct colors, which helped in segmenting the fruit from the background. Fig. 2c illustrates this step, where color segmentation highlights the areas relevant to assessing fruit quality. The software then classified the remaining pixels based on their similarity to the selected reference points

Next, we identified key areas of interest (ROI) within the segmented fruit surfaces, which we referred to as "blobs." These blobs represented natural surface features, such as stems or calyxes, depending on the fruit type, and could also indicate various defects. To pinpoint these ROIs, we manually selected

pixels that best captured the characteristics of both the blobs and the typical fruit surface. Using these selections as references, the software then classified the remaining pixels based on similarity metrics, ensuring accurate identification of relevant features.

## VII. DISCUSSION



**Fig 11 . Graph**

As shown in Graph 11, this survey report provides an overview of previous studies, highlighting their methodologies, accuracy, and publication years. In recent years, fruit counting and detection have gained significant attention, with researchers exploring various techniques such as computer vision, pattern recognition, backpropagation networks (BPN), segmentation methods, texture analysis, yield estimation, and Hough transformations.

Over time, advancements in fruit analysis and detection have emerged through different approaches. In 2006, Mohammad Bagher Lak introduced a computer vision-based method that achieved 90.4% accuracy in detecting and counting fruits. The following year, Zania S. Pothen developed an innovative pattern recognition technique, which reached 82% accuracy in apple counting and 80% accuracy in fruit detection.

In 2008, D. Jayas introduced a neural network approach that significantly improved fruit classification, achieving an impressive 96% accuracy in quality assessment. These studies illustrate the steady progress in fruit detection technologies and the increasing precision of computer vision applications in agriculture. In 2009, M. Jonathan Wu revisited the pattern recognition method and significantly improved its effectiveness, achieving an impressive 94.5% accuracy in fruit detection. A year later, in 2010, K. Paravati introduced a segmentation-based approach that successfully detected and graded fruits with 90% accuracy.

Advancements continued in 2011 when Peilin Li developed a color-based segmentation technique that accurately identified citrus fruits with an 84.2% success rate. In 2012, H.N. Patel applied a machine vision method that achieved 84.1% accuracy in fruit grading. The following year, in 2013, D. Surya Prabha developed a texture analysis technique that improved fruit detection, reaching an accuracy of 84.5%. In 2014, D.S. Gaikwad introduced a yield estimation algorithm that effectively counted fruit with 90.8% accuracy.

In 2015, Amruta Pandit revisited the machine vision approach in her study, successfully recognizing and analyzing fruit quality with an accuracy of 84.4%. Finally, in 2016, Uravashi Solanki introduced the Hough transform technique, achieving an impressive 90.9% accuracy in fruit detection. These advancements

highlight the fruit industry's ongoing innovation and refinement of methods, demonstrating the increasing precision and efficient use of vision algorithms and machine learning in applications related to agriculture.

## VIII. CONCLUSION

Our research aims to explore various approaches and strategies for classifying fruits based on their size. Most existing methods rely on image capture techniques, requiring both a camera and a computer, as highlighted in previous studies. However, these systems come with high initial and ongoing costs and often require a technically skilled operator. As an alternative, we can explore the mechanical and physical properties of different fruits to develop cost-effective and efficient grading machines.

This study examines the basic method of categorizing fruits and evaluation. It discusses how methods like SURF, HOG, and LBP can be used to extract vital characteristics like color, size, shape, and texture. It also discusses the methods of machine learning such as CNN, SVM, ANN, and K-NN, which play a critical part in categorizing. While hardships still exist, automation of vision has begun to emerge as the future of noninvasive fruit assessment and categorization.

Future research could focus on classifying images of locally grown fruits and vegetables, potentially leading to the development of specialized grading machines and algorithms. This technology could also be extended beyond fruits to recognize and categorize flowers, leaves, and plants, offering detailed insights into their characteristics. Further advancements might explore more sophisticated grading features, such as detecting diseases or analyzing the internal texture of fruits.

The significance of picture processing and computer vision in the agricultural sector is highlighted by this article. Superior attributes like shape, size, color, texture, and defects determine the value of the product from the agricultural products.

A computer vision system would thus replace traditional time-consuming inspection processes with a fair, non-destructive, and highly accurate solution. There are four critical steps in the process: image acquisition, differentiation, feature extraction, and categorization. Each step is critical to analyzing and assessing the quality of the produce.

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