International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 14, No.1 (Oct-23)

http://dx.doi.org/10.12785/ijcds/140187

Citrus Fruit Disease Detection Techniques: A Survey and Comparative Analysis of Relevant Approaches

Poonam Dhiman[1], Amandeep Kaur[2] and Vinay Kukreja[2]

[1]*Government PG College, Ambala Cantt, India*
[2]*Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India*

Received 3 Aug. 2022, Revised 6 Aug. 2023, Accepted 21 Sep. 2023, Published 1 Oct. 2023

Abstract: The incorporation of computer vision in contemporary agriculture has witnessed significant advancements, particularly in detecting diseases and deficiencies affecting citrus fruit production. This study provides an in-depth comparative analysis of several limitations of the citrus fruit detection system and the cutting-edge machine vision algorithms used for classification. Traditional diagnostic methods are initially reviewed, followed by an elaborate discussion on various image acquisition techniques such as remote sensing, hyperspectral imaging, bio speckle laser imaging, and color imaging. These techniques focus on extracting features like color, texture, and size for diagnosing citrus fruit diseases. Despite their effectiveness, the images obtained might contain noise and distortions. The study details two crucial steps—image preprocessing and segmentation—to minimize these anomalies. It further explores a range of classification techniques and their efficacy in different research contexts. The paper is structured around five key components: diverse image capture methods, preprocessing and segmentation techniques, various extracted features, classification techniques for citrus fruit detection, and a comparison among classification methods like machine learning, deep learning, and statistical techniques. The study concludes by discussing current challenges and limitations in detecting citrus fruit diseases. It emphasizes the use of thresholding in hyperspectral imaging and identifies RGB color space as a frequently used feature. Among the compared techniques, Support Vector Machine (SVM) in machine learning, Artificial Neural Network (ANN) in neural networks, Convolutional Neural Network (CNN) in deep learning, and Linear Discriminant Analysis in statistical approaches emerge as the most effective.

Keywords: Image acquisition, preprocessing, segmentation, clustering, machine learning, deep learning, statistical techniques

1. Introduction:

Various applications like autonomous vehicles, object detection, face recognition systems, and many more depend upon endeavoring to imitate the capacities of a brain to understand the information given. Indian agriculture is of paramount significance because of the country's expanding population and rising food needs. Therefore, it is necessary to increase crop productivity. One of these significant factors contributing to reduced agricultural yields is the prevalence of bacterial, fungal, and viral diseases. Expert persons visually detect vegetables and fruits to assess the quality of crop production. However, different constraints are there in the case of classification done manually, such as one should be conversant with varying characteristics of vegetables and fruit. Manual detection needs a regular and harmonious approach to maintain efficiency. The food industry applies different detection mechanisms and depends on machine vision to analyze Crop harvesting. By using methods for plant disease detection, this can be avoided and managed. Techniques relied on machine learning will be employed in the procedure of identifying plant illnesses since they apply information most frequently and provide excellent methods for disease diagnosis. Because machine learning techniques focus on data supremacy results for a given goal, they can be used to identify disorders. A limited number of studies during the past ten years have shown how crucially the quality of fruit products affects human wellbeing. Fruit items should form the foundation of a healthy eating plan [1].

The research provides a comparative analysis of several constraints of the citrus fruit recognition techniques and cutting-edge machine vision methods utilized for classification. Background research involves image-capturing procedures, a description of the most widely used preprocessing techniques, different features extracted from the citrus fruit dataset, and classification methods used by various researchers are discussed in Section 2. In Section

E-mail address: poonamdhiman19@gmail.com, amadeep@chitkara.edu.in, onlyvinaykukreja@gmail.com

3, a comparison of classification methods using derived features, various datasets employed, and the detection system's accuracy are shown. Finally, Section 4 presents a more thorough evaluation of the shortcomings of current methodologies and future directions. The study's conclusion is presented in Section 5.

2. Background

Machine vision platforms are indeed a commercial tool for food standards evaluation. All such systems would assess production throughout the domain and be used for robotic post-harvest or the early diagnosis of possibly lethal diseases. It is often used in post-harvest processing for the computer-controlled investigation of the fruits' external quality, including the breakneck speed filtering of them together in commercial sections. Figure 1 illustrates the complete process of disease detection of citrus fruit images, including acquisition, image processing (pre-processing and segmentation), and feature extraction (color, shape/size, textural) followed by the classification process that can use ML, DL, and the statistical techniques(ST). The whole process has used many evaluation parameters to analyse the outcome of the approaches used to recognise the diseases of citrus fruits.

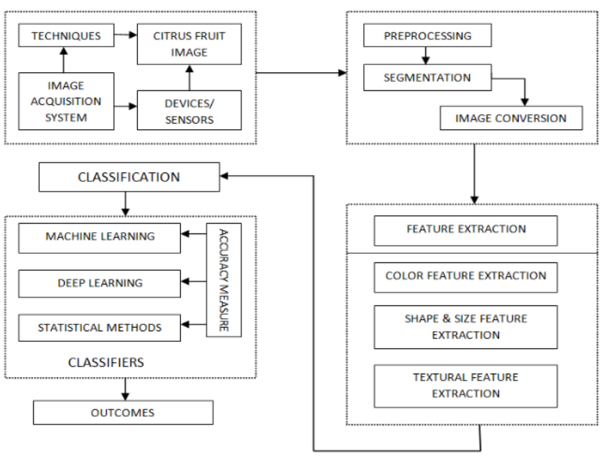


Figure 1. Complete process of citrus fruits diseases detection

A. *Image Acquisition System*

Images are used for acquiring information. Computer vision systems carry out conceptual and algorithmic estimation, allowing useful information about the objects or images to be automatically obtained from the acquired images and evaluated. Multispectral acquisition systems typically scan throughout the 3D while collecting 2D data at a time. Relied on filteration methods like optical filters and automatically adjustable filters, multispectral scanners and imagers are categorized into various types [2]. The most often used acquisition system is a 3CCD camera arranged with a light source utilizing a grey card [3]. Different fusion methods, including features , pixels, and symbolic levels, have recently been created. To identify orange fruits using visible-thermal pictures, researchers have used image fusion [4]. Two separate NIR devices, a micro-NIR and an FT-spectrometer, are displayed in the terms near-infrared spectrometer and spectral acquisition. Using a linear regression model, the two micro-NIR and FT spectrometers were compared [5]. Table 1 shows the acquisition technique, sensors, and devices used by the image acquisition system, along with the wavelength range or resolution used and the spectral band sizes. The studies' main acquisition techniques are remote sensing techniques, hyperspectral imaging systems, biospeckle laser imaging systems, and color imaging systems.

B. *Pre-processing and Segmentation:*

After the image acquisition, the next step is pre-processing. The objective of Pre-processing will enhance the grade of image samples that has unwanted distortion or inflates key features. Because of different photographic conditions, any differential operator highlights the noise without applying the pre-processing step. There exist various kinds of approaches for enhancement, noise removal, filtering, and sharpening of images. The discrete cosine transform method has been used to enhance the image during the grace period [6]. The filtering process is also used on mango fruit images to remove the noise. Background subtraction using thresholding for the determination of the coarse of mango fruit is employed [7]. Radiometric correction is the widely used method for the pre-processing of multispectral images [8]. Pre-processing was first conducted by filter processing followed by an image sharpening process with Matlab R2010b software [9]. Histogram equalization is a widely used technique for contrast enhancement of colored images. It produces the statistics for the contrast and overall intensity distribution of an image. Three different approaches are used for the pre-processing of Landsat imagery of the agricultural area [10]. The first approach employed the gradient magnitude of the image that meets the optimum method for image samples with temporal changes and yielded 100% acceptability. The second approach was thresholding the magnitude of the gradient and achieving 97% accuracy. The third approach used thresholding at the median.

Different acquisition methods can result in noise, distortion, and flickering in image samples, all of which can lower the image quality. As a result, the image cannot properly contribute to the data set. Image processing can therefore be used on the image samples to address this problem. Segmentation and image pre-processing are the two basic procedures used in image processing techniques. There are countless strategies for locating and controlling plant pests and diseases, but image processing employing advanced

TABLE I. Image acquisition techniques addressed in selected studies

Paper	Acquisition Technique	Sensor/Device	Resolution / Wavelength Range	Size/Spectral Band
[11]	Visible–NIR	NIR spectrophotometer, light source; reflectance probe, computer with acquisition software.	650–1050 nm	334 spectra
[12]	Unmanned aerial vehicle remote sensing	The multispectral camera	4.32 pixels/mm	651 × 801 pixel
[13]	Hyperspectral imaging system	Monochrome camera, frame-grabber, Two tunable liquid crystal filters, halogen lamps, aluminum hemispherical diffuser	4.32 pixels/mm	651 × 801 pixel
[14]	Biospeckle laser imaging	Digital camera	5 megapixels	(1920×1080pixels)
[15]	Hyperspectral vision system	Smartphones, compact cameras, DSLRcameras, two liquid crystal tunable filters, and low chromatic dispersion	10 nm	460 nm to 1020 nm
[16]	RGB color imaging system	Digital camera, lighting box including two LED lamps	4320×3240	——
[17]	X-ray imaging	Nikon metrology Gun set, image intensifier, and CCD camera	Pixels	1024 1024 1024 pixels
[18]	NIR spectral acquisition	NIR System 6500	2 nm	700–1100 nm
[19]	Color imaging system	DSC Camera, imaging chamber, and imaging box have the light source of LED, UPS power supply	640 × 480 pixel	——
[20]	Electronic nose system and Electronic tongue system	Apparatus for sampling, a detector set having a sensors grid and software for information gathering using structure identification	——	——
[21]	Diffuse reflectance system	portable spectrometer,optic-fiber probe, Ultraviolet (UV) and mercury lamps	200–900 nm.	1050 spectra (five per sample)
[22]	Visible and short-wavelength nearinfrared	50 Watt six halogen lamps,200 mm fiber optic probe, dimmer circuit, spectrometer	2 nm	——
[23]	Hyperspectral image	Monochrome camera,frame-grabber, Two tunable liquid crystal filters, halogen lamps, aluminum hemispherical diffuser	3.75 pixels/mm	551 × 551
[24]	Hyperspectral imaging	An imaging system based on line scan having an electron expanding CCD, a digital spectrograph, push broom, C-mount lens	400 to 900 nm	280 × 658 for each band.
[25]	Hyperspectral imaging	Thermo electric cooled electron multiplying CCD with size 14-bit, a spectrograph mount with a standard 23-mm zoom lens; halogen light area sources, motorized positioning sample table with controlling software, and spectral imaging software system.	325–1100 nm	700 × 1004 pixels

Continued on next page

Table I continued

[26]	Spectrograph-based hyperspectral imaging	Spectrograph, 150-halogen lamp containing two lighting fibers.	The pixel resolution of 0.58 nm and a resolution of 2.8 nm	422.29 to982.40 nm
[27]	Laser-light backscattering imaging	CCD (charge-coupled device) based camera , five laser diodes, light sources	0.073 mm/pixel	720 × 576
[28]	Colour image acquisition system	3-CCD camera, eight fluorescent tubes, Polarised filters	0.17mm per pixel	768x576 pixels
[29]	Electronic nose system	Computerized gasmixer, a detector set having a grid of sensors, and measurement and pattern recognition software	——	——
[30]	Visible near-infrared hyperspectral	The camera includes a VIS/NIR liquid- Crystal programmable filter	10 nm	1040 x1392 x 44
[31]	color image acquisition system	CCD camera, image frame grabber, six white fluorescent tubes in lightening system, Diffuse reflection plate	0.28 mm/pixel	640 x 480 pixels
[32]	Hyperspectral imaging system	14-bit monochrome camera, an imaging spectrograph, halogen light area sources, electrically controlled sample stage	325–1100 nm	700×1004
[33]	Smart Mobile Diagnosis System	WeChat applet, Nginx server	——	——
[34]	Machine vision	Color CCD camera, C-mount lens, frame grabber card, fluorescent lamps	640 H x 480 Vpixels	——
[35]	Computer vision	Camera, incandescent lamp, Windows10 OS platform with Matlab7.0	——	——
[36]	Near-infrared reflectance system	Multi-Purpose Analyzer, FT-NIR spectrometer, quartz beamsplitter, NIR source with an air cooling system, and a detector (InGaAs).	4cm-1	12 spectra
[37]	Hyperspectralimaging system	High-resolution monochromatic camera with two liquid crystal tunable filters	7 nm	400 to 1100 nm
[38]	Computer Vision system	Direct digital output camera using a Firewire	640 × 480 pixels	256 levels per channel (R, G, B)
[39]	Hyperspectral imaging systems	A monochrome camera has highrange of sensitivity from 320 to 1,020 nm, a frame grabber, and an aluminum hemispherical diffuser containing 12 halogen lamps.	3.75 pixels/mm	551×551 pixel
[40]	The diffused illumination system computervision systems	CCD camera, a lighting system composed of-backlighting and a personal computer	12.1Megapixels	——
[41]	Near-infrared information system	Multi-view camera	24 bits-per-pixel	164x113 pixels
[42]	Computervision systems	NTSC camera, frame grabber, Two fluorescent-circular lights, commercial softwarepackage	787 Kbyte per image	512 x 480
[43]	Computervision systems	Digital camera	——	——

Continued on next page

Table I continued

[44]	Hyperspectral imaging system	Electron-multiplying CCD camera, Peltier device, the lighting system (21 V,150 W halogen lights), Hg-Ne spectral calibration lamp	5.2 nm	1004 x 1002 pixels
[45]	NIR	Kinect for Software Development Kit 2.0	512 by 424 pixels	——
[46]	Color imaging system	Digital camera	——	640 x 480 pixels
[47]	RGB color imaging system	Digital camera	1024 768-pixel	——
[48]	Machine vision system	Two cameras, rollers, cog belt	0.1–g	——
[49]	Fluorescent spectrum system	Fluorometer, digital refractometer	200 to 550 nm	300 to 700 nm
[50]	UAV-based hyperspectral imaging technique	Remote sensing technique, Resonon's hyperspectral imagers, the global positioning system	——	400–1000 nm
[50]	Color imaging system	Digital color camera	——	——
[51]	NIR	Non-destructive sensor+ CCD camera+ digital board+ digital refractometer	3mm x 25mm	770-1070 mm
[52]	Color imaging system	Sony cyber shot camera, dark imaging chamber	4320x3240 pixels	——
[53]	Color imaging system	Sony cyber-shot camera, dark imaging chamber, conveyor belt, actuator	——	——
[54]	Color imaging system	Digital color camera (SonyCybershot DSC-WX300)	——	——
[55]	RGB color imaging system	Digital camera and mobile phone camera	——	——
[32]	Hyperspectral image calibration	Spectral Image Software (Isuzu Optics Corp., Taiwan), CCD detector	500–1050 nm	1007 bands
[56]	Spectral imaging system	Reflection probe holder, light source, spectrometer	0.28 to 0.38 nm	1914wavelengths
[57]	RGB Color image system	Two high frequency sealed fluorescent lights of 13 W, a zoom lens, a 3-CCD RGB color camera, a 24-bit colored frame grabber board	480×640 pixel	100 mm×100 mm
[58]	NIR	CR-200 colorimeter, S2000 spectrometer, four halogen lamps (100W), and an array of lens and optical fibers.	650 [nm] to 955 [nm].	——
[59]	RGB Color image system	CCD sensor camera, two fluorescenttube lamps	——	——
[60]	Color image system	13 MP CMOS camera, illuminationthe system, computer hardware, and camera holder	1920 * 1080 pixels	——

artificial intelligence methods like deep learning is the most popular. In some circumstances, data retrieved from sensors or other inputs are added to picture processing. A method for detecting citrus fruit diseases based on lightweight artificial intelligence approaches was reported in certain studies. This system used edge computing to process all the data on the cutting-edge Raspberry Pi. The authors contrasted clear photos of both healthy and diseased rice leaves on a white backdrop. The relevant features were retrieved from the images after the appropriate pre-processing. Following that, using various machine learning methods, image categorization models were created based on these attributes [61].

The segmentation of an image area is an essential activity for image processing. For the computer vision system, segmentation is the procedure of clustering the pixel into salient regions with certain properties. Image segmentation is also referred to as assigning a label to pixels of an image such that these labeled pixels help in sharing some visual features. Various approaches like thresholding, region growing, k-means clustering, and watershed have been used to estrange the lesion areas affected by anthracnose diseases in fruits. For an x-ray imaging system, the gray level of the pixels relies on the thickness and the density of the images [62]. Segmentation of the color image samples has been carried out in two stages, in the first step, a 2D feature map captures the dominant color of the images in supervised mode, and in the second step, a variable size 1D feature map and color merging was used to regulate the clusters range [63]. Various color spaces for segmentation and color images have been designed for data acquisition. For the automated image segmentation of the colored images of fruits, CIELuv color space was used. The color space of the CIELuv is qualitatively consistent and the color space is system independent.

The images acquired by the image acquisition methods may contain noise, distortion, and variability. To reduce these deformities among raw images two major steps i.e. image pre-processing and image segmentation. Table 2 shows the name of various pre-processing techniques used by the studies in our SLR. Majorly used techniques employed by the studies are scaling, normalization, image enhancement, filtering, thresholding, masking, histogram equalization, transformation, transformation, morphological operation, watershed, k-means, ostu based segmentation techniques that depict in the table also. Apart from the techniques mentioned in Table 2, some other techniques are also used by various studies like edge/boundary detection for the segmentation purpose, color segmentation, gradient method, wavelet transformation, and c-mean clustering. The most widely used image processing techniques used are image enhancement/filtering followed by thresholding**.**

C. Feature Extraction:

Several visual characteristics associated with fruit and vegetables are called features. Initially, fruit images are captured by the camera, and then pre-processing and segmentation methods are used on the imagery. to filter, smoothen, and remove the noise images. After these steps, feature extraction takes place which further helps to classify the diseases. Color is the most persuasive aspect and substantial descriptor that frequently improve feature extraction for image analyses of fruits and vegetables. Color features perform a crucial part in detecting or classifying the disease of the fruits. Different color space like HSV, RGB, HIS, and YCbCr is employed for classification purpose. Color features are more considerable than other features because of invariance to shape, size, and direction, simplicity in the extraction process, and background complexity individualisms [64]. Images are transformed into a different colour space to depict more desirable aspects that are not striking in standard RGB space. In this study, the L*, a* & b* component value of the image is taken to get the LAB color space. By using a histogram on the segmented image the color feature has been extracted [65]. Two important size features area and perimeter can also be evaluated by getting the pixel count of the images and by adding up the distance of each adjacent pixel at the boundary respectively. For food and vegetable quality analysis most common size features are area, perimeter, length, and width. Apart from these features, major axis, and minor axis features can also be determined for classification purposes. The major axis is the largest line through the fruit or vegetable product which is determined by the measurement of the distance between the two boundary pixels of each mixture and chooses the longest distance. The longest line formed perpendicular to the major axis by the entity is considered the minor axis [66]. For a broad variety of images that utilize human visual frameworks for identification and perception, the texture is indeed a quite suitable classification feature. The textural feature computed from the pixel group reflects the dissemination of components and the morphology of the surface and is useful for computer vision that determines the surface in the context of entropy, roughness, orientation, contrast, etc. The interior condition of the fruits and vegetables, including growth and sugar component, is consistent with the textural feature [67]. Numerous features can be utilized to depict an item, which is further contrasted with the details collected from non-object for the classification into different classes. Usually, the most sustainable features that are simple to measure and significantly contribute to the classification are the best [68].

TABLE II. Summary of image processing techniques

	Scaling/ Normalization	**Noise Removal**	**Image Enhancement/ Filtering**	**Thresholding**	**Masking**	**Histogram equalization**	**Transformation**	**Morphological operation**	**Watershed**	**k-means**	**Ostu based**
[12]		✔	✔								
[17]		✔	✔								✔
[19]				✔							
[23]			✔								
[24]					✔						
[25]			✔	✔			✔		✔		✔
[26]	✔		✔	✔	✔			✔			
[28]	✔			✔	✔	✔					
[29]											
[30]				✔			✔				
[31]			✔	✔							
[32]			✔								
[34]	✔		✔							✔	
[35]			✔	✔		✔					
[38]		✔		✔	✔						
[39]				✔	✔						
[40]	✔										
[41]				✔			✔	✔			
[42]				✔							
[43]	✔			✔		✔					
[44]				✔							
[45]			✔								
[46]			✔	✔		✔					
[69]				✔				✔	✔		
[50]				✔	✔						
[47]				✔					✔		
[48]	✔										
[49]											
[50]		✔									
[52]										✔	
[70]			✔								
[53]		✔	✔								
[55]	✔										
[57]							✔				
[60]	✔			✔		✔	✔				
[61]			✔	✔				✔			
[71]	✔	✔	✔		✔						
[72]		✔							✔		
[73]			✔	✔					✔		
[74]			✔				✔			✔	
[75]			✔	✔							
[76]					✔						
[77]		✔	✔								✔
[78]			✔							✔	
[79]			✔							✔	
[80]			✔							✔	
[81]			✔	✔							
[82]			✔	✔							
[83]		✔	✔								
[84]		✔	✔							✔	
[85]		✔	✔								
[86]		✔	✔								
[87]										✔	✔

1) Color Feature:

Different color spaces are constituted by colors like RGB, HIS, HSV, YIQ, and YCbCr. The description of various color features used in selected studies is mentioned in Table 3. The most commonly used color space is RGB color space which consists of red, green, and blue elements of the picture. HIS color space has three components i.e. hue (H) which is an angular value that constitutes the predominant wavelength of color, the second component saturation (s) indicates the quantitative aspect of color and the third component intensity which is the ratio of darkness/brightness of color.HSI color space can aberrantly recognize the segments of color and diminish the complex color dimensions [88]. YIQ color space represents one luminance component and two chrominance components depending upon the difference in color signal (R-Y, B-Y).three components of YIQ space correspond to y(luminance), I(in-space) and Q is the quadrature that combines to represent hue and saturation [89]. In the YC_bC_rcolor space, the Y component is similar to the Y component of the YIQ color space. By using reduced spatial resolution and coarser quantization for C_b& C_r greater compression is achieved. The authors show that using the RGB color space effect of light causes a false detection area which will result in poor defect detection. YC_bC_r color space is used which produces a better result as compared to RGB space [69]. This paper also uses a linear regression model that indeed classifies undefined orange samples and also estimates the maturity of the orange fruit. Table 3 represented the various color spaces and color models used by different investigations on citrus fruits.

2) Shape/size feature:

The outcome of the total perimeter is 39.46 and 445.28; the area perimeter is 23.21 and 13.43 using transversal and axial radiographs respectively. Different types of shape/size features were used in different studies for citrus fruits for classification analysis the normalized delta and delta^{2}values along with ($di_{polar}/dia_{equator}$) shape factors were used [42]. The area which is defined as the overall image pixels of orange fruit and the circumference of the total count of edge points are calculated for the shape feature. A comparison between the extracted features from an axial and transversal radiograph of endoxerated lemon fruit is conducted [17]. Different shape features are derived using binary images in the study [51]. Using multiple linear regression, size features like length and width of the principal axis are measured with the employed algorithm while polar and equatorial diameters were determined manually. The study shows that the area parameter has a higher correlation with manual measurement after investigating the relationship between the area obtained with the vision system and two manual measurements. The correlation coefficient between manual and vision measurement of the major axis is 0.82, the minor axis is 0.84 and the area is 0.091 [6]. The $diameter_{polar}$ shows the stem-to-blossom end computation. The shape factor based on the equatorial/ polar diameter ratio was the input neural net analysis. Shape features such as perimeter, area, minor, and major axis length are calculated [43]. Using neural networks correlation coefficient remains low for predicting the maturity of orange fruit. So it is difficult to get the growth of oranges with selected non-destructive sensors. The small deviation is the perimeter-area function method used to calculate the fractal dimension of disease and pest hazards. Perimeter-area fractal dimension is derived according to B.Mandebrot fractal theory. Two surface defects i.e. white streaks and black rot points are detected in orange fruit [35]. The RGB image is transformed into grayscale for the computation of the shape feature. After that, the grayscale image gets transformed into a binary image depicting the value above the threshold is treated as 1, and a value below the barrier is treated as 0. Table 4 shows the various extracted shape/size features used in the selected studies.

3) Textural Features:

Textural features are one of the most widely used features for image ranges that have a visual system of human identification and explication. Textural feature from the pixel set shows the element distribution and appearance. It is also beneficial in the application of the machine vision system that depicts surface features like orientation, contrast, entropy, roughness, etc. textural properties that have compatibility with internal qualities like sugar content as well as the maturity of the fruits. It segregates various image patterns by considering values intensity magnitude. Table 5 shows the various extracted textural features used in the studies.

3. Classification and Comparative Analysis:

The quality of agricultural products is significantly lowered as a result of plant diseases and pests. Pests like Mediterranean fruit diseases, one of the most significant plant pathogens, seriously harm crops, costing farmers a lot of money in lost produce each year. Therefore, it is crucial to utilize contemporary, non-destructive approaches to identify pests in agricultural goods as early as possible. Examples include machine vision systems and deep learning [90], [91]. The Neural Network is a technique inspired by and analogous to the human nervous system and brain structure. It constitutes units of processing divided into layers of input, hidden, and output. Neural networks hit a dark phase in their evolution in 1969, rather than experiencing further research and growth, while professors at MIT illustrated that they could not learn a basic XOR function [92]. Besides, several other studies have blunted the motivation for DNN in particular [93], [94]. A revolution in DNN emerged with the introduction of the learning algorithm for back-propagation. It was suggested in the 1970s, but it wasn't completely understood and extended to neural networks until the mid-1980s.

TABLE III. Different color spaces used for different fruits and their color model used.

Paper	Fruit type	Color space	Color model
[19]	Oranges	RGB	Ravg, Bavg, Gavg, and maturity/ripeness measure
[35]	Orange	RGB	Mean R, G, and r-g values and standard deviation
[38]	Oranges	RGB	Histogram of each color component
[41]	Orange	(RGB) and RGBI	RGB, Hue-Saturation-Intensity, and X-Y Lightness model
[42]	Grapefruit, orange, tangerine	HSI	Color standard location and calculation of color standard values
[43]	Orange	HSV	Hue, Saturation, and Intensity-based
[45]	Hamlin sweet orange	RGB, NIR	circular Hough transform
[46]	Oranges	HSV	mean and standard deviation
[47]	Orange	RGB	Watershed on RGB, Border/Interior pixel Classification (BIC) (logarithmic distance (dLog) and extract (mean gray value)
[48]	Orange, grapefruit, or tangerine	HIS	Macbeth color checker
[50]	Oranges	HSV and YIQ	S and I component from HSV and YIQ domain
[51]	Oranges	RGB	Colorimeter
[52]	Kinnow	RGB, HSI	12 features derived from R-G-B channels, Hue, Saturation, and Intensity. Mean and Variance of each of the six components.
[53]	Orange	HSV	Histograms analysis of the r-g-b and the gray levels, Mean and median evaluation from HSV color space
[54]	Orange	H SV and YIQ	Mean, variance, and range values calculated from the separated S and I components
[55]	Lemon	CMY	The pixel count of the red, green, and yellow component
[57]	Grapefruits	HIS	Coordinates of chromaticity in the hue and saturation space
[59]	Bitter orange	RGB and CIE	Color matrix statistical parameters (R- G- B), or their variations and proportions, & three CIE parameters (L*a*b *)
[61]	Citrus fruits	RGB, HSV, HSI, LAB, and LUV	All color characteristics are eventually merged by basic convolution into one vector and achieve a size 1 to 60 function vector
[71]	Oranges or tangerines	HSV (Hue, Saturation, Value)	Low and the high hue values
[69]	Navel Orange	RGB, YCbCr	Gray distribution mapping
[70]	Apple, oranges, mangos, watermelon	RGB	Mean Intensity
[72]	Orange	RGB	The mean value of RGB channel splitting
[73]	Newhall navel oranges	RGB	Watershed on RGB
[74]	Mandarin Orange	L*a*b*	Color coherence vector and Global color histogram
[76]	Apple and Kinnow fruit	L*a*b*, HSV, HSI	Binary masks for hue and saturation channels, extraction of V-Channel of HSV model
[78]	Orange	RGB	Conversion of RGB color space into HSI color space, translating the Hue value to degrees on the color circle
[85]	Apple, avocado, banana, and orange	RGB	Kernel of Gaussian values
[86]	Persian lemon	HSV	Number of pixels of the fruit, as well as the sum of the small areas that represent the present defect
[87]	Orange and potato	L*a*b* or CIE-Lab	Euclidean color distance
[95]	Lemon	L*a*b*	Mean shift vector
[96]	Tangerine	RGB and HSV	Nonlinear transformation of the RGB

DNN is a type of multilayer perceptron (MLP) modeled neural network that is trained through methods for learning depictions from data sources without even any manual feature extractor model. It consists of a larger or deeper number of processing units, as the term Deep Learning implies, which compares with the shallow learning paradigm of fewer unit layers [98].

Table 6 represents the name of the techniques which outperformed the other ML techniques. SVM is the best technique that performed better than W-KNN, EBT, DT, naïve bayes, fuzzy, and RBF techniques in six different experiments. The second best-performed technique is the decision tree in 5 different experiments as compared to the naïve bayes, RB, fuzzy, EBT, and SMO. We found that the AdaBoost ML technique is a very less explored technique in the field of citrus fruit disease classification. Adaboost ML technique was used in only one study and outperformed many ML and DL techniques. Lastly, some more techniques like the random forest, KNN, ELM, and FA were also found to be well-performed ML techniques.

Similarly, in some experiments, ML techniques performed better than other DL techniques. Like, SVM again performed better than DL techniques such as ANN, CNN, and MLP in 5 different experiments. Table 7 shows ML techniques that performed better than the DL techniques. Here, we observed the DT, Bayesian, Adaboost, KNN, W-KNN and ELM also performed well than DL techniques in 1 or 2 experiments.

Table 8 shows ML techniques that outperformed the other statistical techniques like LDA, PCA, and LR. Look at table 9 which shows DL techniques that outperformed ML techniques. It can be observed that ANN and CNN are the two best techniques that performed better than the ML techniques in 5 and 2 experiments respectively. We also found that other DL techniques like neural network radial basis; Associative neural net and backpropagation neural networks outperformed the other ML techniques in different experiments.

Table 10 mentioned statistical techniques that performed well when compared to the other techniques. It can be observed that the LDA technique is the best technique among all the statistical techniques in comparative studies of our SLR. Other well-performed statistical techniques we found arePartial least square regression, PCA and LR.

A. Summary & Findings of Comparative Analysis:

The use of extra spatial characteristics aids in improving the classification accuracies of the approaches in citrus fruit classification, as can be shown from the comparison study of ML and DL techniques. CNN uses rich spatial features at various scales to represent the spatial structure of the data to categorize each pixel in the image since spatial information can increase classification accuracy.

When DL and ML techniques are compared, it becomes apparent that most of the relevant features in traditional ML techniques must be determined by an expert in the field so as to decrease the complexities of the information and render correlations readily apparent to learning techniques. The primary advantage of DL algorithms is their aim to gradually learn complex features from data. This eliminates the need for rigorous feature extraction and domain expertise.

It becomes evident that both SVMs and NNs are capable of doing classification, with the SVM requiring the proper choice of kernel and the NN requiring the proper choice of the activation function. When the pixel-based reflectance data were employed, lacking the segmentation measurement, CNN was found to have a static-major gain over SVM in terms of overall correctness. In both SVM and CNN classifications, the impact of pixel-based training data was considerable. As a difference in sample size, object-based training samples differ from pixel-based training samples. Although, if the total sample count is the alike for both types of samples yet pixel-based reflectance data give trained classifiers access to more spectral reflectance values.

As a result of maximizing classification accuracy, LDA decreases the dimensionality of the data, making it more efficient than PCA for classification datasets. Drawing decision lines for data with the greatest degree of separation is simpler. Using the citrus fruits classification dataset, it has been found that the LDA is significantly more successful than PCA for dimensionality reduction in classification datasets.

Table 11 shows the type of dataset used for the research work by different studies, along with their accuracies obtained. Many researchers have used private data by acquiring the images using different image acquisition systems like UAV-based systems, multispectral systems, and remote sensing systems with the help of digital cameras or sensors for the particular area or orchards. In some studies, citrus fruits are inoculated into chemical solutions for fungal diseases. The studies that commonly used Public data sources are the Kaggle dataset, plant village, www, andCitrus image Gallery dataset.

It is noted that around 73 % of the selected studies were published in journals, while the rest were published in conference proceedings (i.e., 27 %). Postharvest Biology and Technology and Computers and Electronics in Agriculture are the two foremost journals that have been published in 8 and 6 studies selected in the SLR. These two journals published around 19% of all the chosen publications that examined the intended area of the study. We consider here only those journals which have been indexed as Science Citation.

TABLE IV. Measuring parameters of different feature matrices.

Paper	Fruit type	Feature matrix
[17]	Oranges, lemon	Overall perimeter, average solidity, and proportion of the complete area to the perimeter
[25]	Oranges.	Area, perimeter, and circularity
[35]	Orange	Area, circumference, size
[42]	Grapefruit, orange, tangerine	Center-finding routine, eight radii, perimeter tracing, shape factor ratio, area normalized values for delta and delta2values, (diameter.ˆ,./diameterequator)
[43]	Orange	Major and minor axis length, perimeter, the image area
[46]	Orange	Major and minor axis length, perimeter, area
[69]	Navel Orange	Surface area and coloring area
[51]	Orange	Length, width, elongation, circularity, major axis length and minor axis length, width, length, area, perimeter
[53]	Orange	Area, fractal dimension, box-counting dimension,
[55]	Lemon	Area, Major axis, and Minor axis
[60]	Apple, litchi, mosambi, pomegranate, and pears	Major and minor axis, mean, convex area, diameter, solidity, area, perimeter
[61]	Citrus fruits	Major and minor axis, extent, area, perimeter, filled area, aspect ratio, and solidity
[73]	Newhall navel oranges	Perimeter and area with pixel count,perimeter-area fractal dimension
[82]	Nova mandarins	Circular spot, Deepness Shallow,
[83]	Mandarin	Discriminant relevance of feature, z statistic of feature, global relevance of each feature
[86]	Persian lemon	Equatorial diameter, surface area of the lemon, percentage of area with defects, Persian lemon

TABLE V. Textural Features

Paper	Texture Feature	Descriptor	Fruits
[11]	1570 spectral Features (visible–NIR and NIR)	Scatter-correction methods	Mandarin
[14]	Regular value of differences (RVD), the absolute value of differences (AVD), modified AVD (NUMAD), and Inertia moment (IM)	Co-occurrence matrix (COM)	Orange
[15]	For each spectral band pixel reflectance degree, average reflectance and standard deviation of a pixel cluster	57 spectral features, 114 spatio-spectral features	Tangerines
[30]	Mean, variance, skewness, kurtosis, range	First, second and high order statistics	Oranges
[34]	Mean, standard deviation	Wavelet Packet Texture analysis	Mandarin fruit
[40]	Mean, std_dev, energy, entropy	Four statistical curvelet-based texture descriptors	Lemon
[41]	Minimum, maximum, range, arithmetic mean, range and standard deviation	Spatial variation in pixel intensities/ statistical feature	Orange
[43]	Angular Second Moment, Contrast, Correlation, Gradient Module, Intensity symmetry	Five textural features derived from the gray-level co-occurrence matrix	Orange
[44]	Reflectance spectra of the five peel conditions, the two-band ratio, and the band difference	92 spectral bands.	Valencia Oranges
[45]	Divergence and vorticity values	Gradient vectors of depth values	Hamlin sweet orange
[46]	Geometric and harmonic mean, variance, standard deviation, mean, median, range, and (Angular Second Moment, Contrast, Correlation, Gradient Module, Intensity symmetry)	Gray level co-occurrence matrix, histogram statistics	Orange
[50]	Mean, SD, skewness, kurtosis, energy, entropy, correlation, prominence, homogeneity, the sum of the square, etc (44 feature)	First-order statistical texture features, second-order Gray level co-occurrence feature	Oranges
[53]	Contrast, Correlation, Energy, Homogeneity, Skewness, Kurtosis	Six statistical descriptors with occurrences gray level matrix.	Orange
[54]	Brightness, contrast, uniformity, flatness, smoothness, contrast, correlation, cluster prominence, dissimilarity, autocorrelation, maximum probability, energy, the sum of squares, sum average, sum and difference variance, sum and difference entropy, maximal correlation coefficient, entropy, cluster shade, homogeneity, information measures of correlation 1 and 2, inverse difference, normalized inverse difference moment normalized and inverse difference	First-order and second-order statistical features using the GLCM method	Orange
[57]	Uniformity, variance, product-moment, mean intensity, correlation, sum entropy, entropy, difference entropy, modus information correlation #1 and #2, contrast, and inverse difference	All of the other three SGDM, 13 texture characteristics for each part of the HSI	Grapefruits
[61]	cluster prominence and shade, homogeneity, energy, Mean, range, skewness, and entropy	18 GLCM features	Citrus fruits
[69]	Smoothness descriptor , consistency measure , and the average entropy descriptor	Grayscale with statistical feature	Navel orange
[74]	Correlation, mean, entropy, RMS, contrast, variance, energy, standard deviation, smoothness, kurtosis, IDM, skewness, and homogeneity	Thirteen textural features are extracted from GLCM	Mandarin Orange
[78]	Minor wavelet, major wavelet.	2-D deviation of a grey level	———
[82]	Depressed or Prominent Topography of the surface, Ruggedness of the central surface, Central texture		Nova Mandarins
[84]	Contrast, correlation , entropy, homogeneity, and energy	Gray-level co-occurrence matrix	Banana, Mango, Citrus, Grape, Guava, Apple, Papaya, Peach, Watermelon Pomegranate
[85]	Correlation, energy, homogeneity, contrast, entropy, Mean, variance, skewness, kurtosis, range, IDM	Statistical features,gray-level co-occurrence matrix	Apple, Avocado, Banana, and Orange
[96]	Mean, variance, skewness, kurtosis, range	First, second and high order statistics	Tangerine
[97]	Mean, standard deviation, and skewness	Reflectance parameter and reflectance distribution parameters	Thompson and Jaffa Oranges

TABLE VI. ML techniques that outperformed other ML techniques

ML Best Technique	Outperformed ML Techniques					
SVM	W-KNN, EBT, DT [61]	KNN, SRS [83]	KNN, Naïve BaYes [12]	DT, Fuzzy [16]	RBF [53]	KNN [99]
DT	Naïve BaYes [47]	RB [53]	Fuzzy [16]	EBT [61]	SMO [53]	
FA	SM [11]					
Adaboost	SVM [12]	KNN [12]	Naïve Bayes [12]			
RF	SVM [20]					
KNN	FUZZY,DT [16]					
W-KNN	EBT [61]					
ELM	SVM [20]					

TABLE VII. ML techniques that outperformed DL techniques

Best Technique	Outperformed Techniques				
SVM	ANN [78]	CNN [60]	ANN [83]	ANN [16]	MLP [53]
DT	ANN [47]	MLP [53]			
BaYesian	NN [42]				
Adaboost	NN [12]				
KNN	CNN [60]				
W-KNN	EBT [61]				
ELM	SVM [20]				

TABLE VIII. ML techniques that outperformed Statistical techniques

Best Technique	Outperformed Techniques	
SVM	LDA [61]	
DT	LDA [37]	
FA	PCA [11]	SM [11]
Adaboost	LR [12]	

TABLE IX. DL techniques that outperformed ML techniques

Best Tech-nique	Outperformed Techniques							
ANN	SRC [83]	SVM,LR, [12], [14]	DT [16]	Naïve BaYes [47], [12]	KNN [16], [83]	FUZZY [16]	LDA [14]	QDA [14]
CNN	KNN[99]	ANN, DT, FUZZY [16]	SVM [16],[99]					
NNRB	KNN [50]							
ASNN	SVM [54]	BPNN [54]						
BPNN	SVM [54]							

TABLE X. Statistical techniques that outperformed other ML techniques

Best Technique	Outperformed Techniques		
LDA	PCA [29]	EBT [61]	CART [23]
PLS	MLR [58]		
PCA	SM [11]		
LR	SVM [12]	Naïve baYes [12]	KNN [12]

TABLE XI. Datasets and Classification Accuracy of the selected studies

Dataset	Accuracy	
117 mandarins with 67 were peripherally ruptured on the rind and immunized with P. digitatum fungus spores and the rest 50 were damaged in about the same manner and handled for process control with sterile water.	97.8%	[11]
334 citrus image samples consist of healthy as well as infected images with HLB disease	97.28%	[12]
13,680 monochromatic images of the 240 mandarins (60 fruits does not exhibit any noticeable disruption, 60 fruits had typical disruption inflicted by wind scars, 60 fruits were immunized with P. digitatum unit, other 60 fruits were immunized with P. italicum solution	93% spores 60 fruits were inoculated with a solution of P. italicum spores	[13]
Biospeckle images	100%	[14]
Tangerines fruit samples	98%	[15]
341 sour lemon images with data augmentation applied(2960 healthy and 2496 un-healthy sour lemon samples)	100%	[16]
30 orange samples and 38 lemon fruit with diverse nature of the infections	95.7% of oranges and93.6% of lemons	[17]
In 2017, Tangerines were taken twice. On 20 June 2017, the first sample collection of 97 late-harvested fruits was retrieved. On 3 August 2017, the second sample collection (178 fruits) was obtained (early harvested fruit)	——	[18]
160 Orange fruit samples	89.9% Edited multi-Seed-NN(Nearest Neighbor) and 92.93 % Nearest Prototype	[19]
Six styles of fruit exhibit blemishes were collected as target items, including oil stain, HLB, wind scar, rust mites, leafminer damage, and melanose. 30 fruit samples were gathered for each form of blemish also healthy fruit samples were collected	Classification accuracies for healthy mature citrus obtained is 98.4%, HLB 90.8%, melanose-95.2%, oil spot 92.0%, wind scar90.8%, and leaf-miner 95.2% and rust mite 96.8%	[21]
165 grapefruits	92.70%	[24]
210 samples of naval orange having 80 healthy and 130 defective fruits	98.60%	[25]
Early-ripe citrus fruit images from China (Wenzho)	96.50%	[26]
For the tests, 100 orange fruits were taken from which 50 were vaguely damaged on the epicarp and immunized with P. digitatum spores, and 50 other were infected in the same manner but handled for process control with sterile water	96.10%	[27]
20 images of oranges and mandarins from four distinct varieties were randomized: Fortune, Marisol, Clemenules, and Valencia120 varieties of randomly chosen orange and mandarin images belonged to four separate cultivars: Valencia, Fortune, Clemenules, and Marisol	91.50%	[28]
Ripe and Non-infested 'Shangtangju' mandarin (Citrus reticulate Blanco). 20 samples were classified randomly into two categories of control and infested pests classes	98.21%	[29]
Eight distinct orange and mandarin variants were studied, including Clementine, Blood Orange, Washington Navel, Miro, Nova, Salustiana, Nadorcott, and Navel Lane Late. 100 fruits of each type were immunized with a concentration of 106 P. spores/ml. The Digitatum. The fungus class is represented by these citrus fruits. The remaining 50 fruits have been liquid-inoculated and constitute the control community	91.00%	[30]
160 citrus fruits, comprising 80 sound fruits and 80 defective fruits with P. digitatum fungi spore	For the training set and test set 97.5% and 93.8% with no false negatives	[32]
Network, local materials, images of fruits with 6 common diseases, and data augmentation	89%	[33]
Mandarin fruits images	50% stem-end rot, pitting 80%, Splitting 100%	[34]
Orange images	95.00%	[35]
54 citrus yielded in Huangyan were collected	80%	[36]

Continued on next page

Table XI continued

20 Mandarins and Clemenules Cv. Clemenvilla.	95%	[37]
1500 images of 150 oranges from “navel-late” and “Valencia-late”	62.1-100% for the range of defects	[38]
A maximum of 240 fruits were used: 60 that were sound, 60 that had exterior scars, 60 that had been immunized by P. digitatum spores, and 60 that had been injected with P. italicum microbes	89%	[39]
1040 lemons	91.72%	[40]
1400 orange (338 healthy images, 441 stem-ends and 621 have bruise of different sizes)	81% 2	[41]
443 grapefruit, 1,417 oranges, and 352 tangerines	Grapefruit-73.9 %,Orange-87.3 %, Tangerine-84.7%	[42]
400 orange images acquired by the rotation and rearrangement of fruit samples	The overall error of 2.75%	[43]
200 valencia orange samples	92%	[44]
Hamlin sweet orange (citrus sinensis) 255 images	96%	[45]
400 orange samples were produced by spinning and reorganizing fruit sample data.	88%	[46]
125 unripe orange images, 85 ripe fruit images, and 125 scaled or rotten orange images	93.13%	[47]
Tangerine varieties Florida grapefruit and orange	98.5% for grapefruit and orange and 98.3% for tangerine	[48]
47 citrus fruits(Satsuma mandarins)	Absolute error 2.48	[49]
Images of immature (green) fruits and tangerine sugar belle leaves were taken from an experiment orchard at Immokalee, Florida, USA	96%	[50]
320 oranges image (salustiana)	Maturity index=0.31	[51]
303 images Kinnow mandarin fruits from Punjab Agriculture University, Ludhiana (India)	98.66%	[52]
32 images of healthy oranges, 30 samples of medium-quality oranges, and 31 images of low-quality or faulty	MLP-84.9%,RBF network-83.9%,SMO-86.0%	[53]
Orange samples of 100 healthy and damaged were hand-picked across orange farms over Nilgiri hills, Tamil Nadu, India	94.50%	[54]
104 CBS positive citrus fruits and 30 CBS negative samples	93.40%	[56]
A total of 180 grapefruits were harvested with healthy and five infected peels	96.00%	[57]
For the maturity trial, 100 ’Unshiu’ citrus fruits were assigned and the remaining 200 fruits were used for the fault experiment.	97%	[58]
2000 samples of different fruits including the litchi, pears apple, pomegranate, and mosambi were generated	99%	[60]
5632 citrus disease images image samples from Gallery Dataset and Plant Village dataset	96.90%	[61]
Tree image of citrus fruits	93.30%	[71]
110 navel orange samples	93.30%	[69]
Infected fruit images of Vidharbha Region, India	400 orange samples were produced by spinning and reorganizing fruit sample data	[70]
200 ripe and 200 unripe image samples of citrus	90%	[72]
324 Newhall oranges with infections and pests	85.51%	[73]
Database of the University of California Agriculture and Natural Resources	90%	[74]
Totaling 68 images, there are 20 healthy oranges, 20 Melanose illnesses, 19 Citrus Canker, and 9 Brown Rot.	93.21%	[75]
Total images - 150,Canker-78 ,scab -15,greening-16,Black Spot-19,healthy-22(Citrus Image Gallery dataset)	97.29%	[77]
Kaggle datasets	88.96%	[78]
Images of five types of defects in orange fruit	67.74%	[79]
Four infected type orange specimens from the University of California Agriculture and Natural Resources database	90%	[80]

Continued on next page

Table XI continued

74 mandarin fruit images	83.30 %	[81]
212 mandarins samples having 43 black spots, 54 citrus canker, 45 scabs, and 70 other (nonquarantine) diseases from a Nova cultivar	83%	[82]
Apple, avocado, banana, and orange images from Kaggle.com	80.00% (k-NN),91.03% (ANN)	[83]
243 images from www	84.66 % C-mean,87.4651% k-mean	[84]
320 images, of which half correspond to lemons in good condition and the other half are not suitable for consumption according to established standards	98.25% for the classification of fresh lemons and 93.73% for spoiled lemons	[86]
800 images, including 400 samples of good appearance, 120 stem-end i, 80 stem-end	97%	[95]
RGB space and HSV (Hue, Saturation, Value) OF 1500 images of 180 orange fruits from "navel-late" and "Valencia-late"	62.1-100%(RGB) AND 62.8-100% (HSV) for the range of defects	[96]

TABLE XII. Dominant journals

Sr.No.	Journal Name	Count	Type	Impact Factor	H-Index
1	Postharvest Biology and Technology	8	Science Citation Index Expanded	4.4	132
2	Computers and Electronics in Agriculture	6	Science Citation Index Expanded	3.858	104
3	Journal of Food Engineering	4	Science Citation Index Expanded	4.03	167
4	Expert Systems with Applications	2	Science Citation Index Expanded	5.452	184
5	Applied Engineering in Agriculture	1	Science Citation Index Expanded	0.973	51
6	Biosystems engineering	1	Science Citation Index Expanded	3.59	100
7	Chemometrics and Intelligent Laboratory Systems	1	Science Citation Index Expanded	2.303	117
8	Cluster Computing	1	Science Citation Index Expanded	2.04	41
9	Current Science	1	Science Citation Index Expanded	0.756	110
10	Electronics Letters	1	Science Citation Index Expanded	0.97	142
11	Food Analytical Methods	1	Science Citation Index Expanded	1.17	40
12	Food Bioprocess Technology	1	Science Citation Index Expanded	3.2	76
13	Food Chemistry	1	Science Citation Index Expanded	5.399	242
14	Horticulture	1	Emerging Sources Citation Index	3.176	10
15	Horttechnology	1	Science Citation Index Expanded	0.63	52
16	IEEE Access	1	Science Citation Index Expanded	4.098	86
17	International Journal of Agricultural & Biological Engineering	1	Science Citation Index Expanded	0.25	26
18	International Journal of Engineering and Technology	1	Emerging Sources Citation Index	0.21	24
19	Journal of Ambient Intelligence & Humanized Computing	1	Science Citation Index Expanded	3.42	28
20	Journal of Integrative Agriculture	1	Science Citation Index Expanded	1.337	40
21	Journal of Scientific & Industrial Research	1	Science Citation Index Expanded	0.32	49
22	Journal of the Science of Food and Agriculture	1	Science Citation Index Expanded	2.463	131
23	Plant Physiology and Biochemistry	1	Science Citation Index Expanded	3.72	113
24	Remote Sensing	1	Science Citation Index Expanded	4.118	99
25	Scientia Horticulturae	1	Science Citation Index Expanded	2.769	102

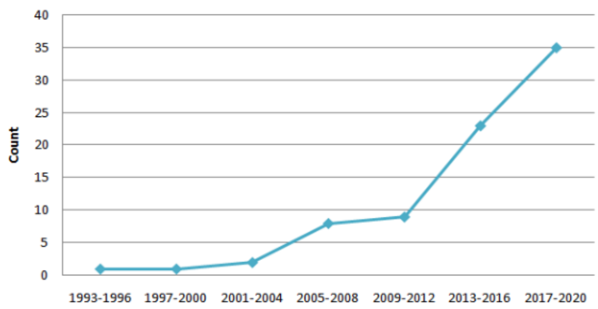


Figure 2. Distribution of selected studies

Table 12 shows the name of the dominant journal, including its impact factor and H-index. It can be observed that the Expert Systems with Applications journal has the highest impact factor, 5.452, contributing 2.5 percent of the total study count of our SLR. Food Chemistry is the second most journal having an impact factor of 5.399 with the highest h-index value of 242.

Publication sources are postharvest biology and technology, remote sensing, and journal of food engineering journals that impact factors 4.4,4.118, 4.03 respectively chosen in SLR. Figure 2 shows the division of different studies of this SLR from 1993 to 2020.

4. Limitations and Future Applications:

The paper provides a current analysis of the classification of citric products and essential procedures based on the literature. Earlier attempts have been widely documented. There are significant obstacles to solve regarding data-acquiring products, modeling features, and identification techniques. Sensors utilized in data collecting in the agribusiness are limited owing to significant constraints in diverse contexts. Several instances are non-destructive, contain ambient obstructions, and exhibit cross and intra-class similarities as well as complicated attributes. An additional key drawback of using numerous sensors in the same citrus fruit analysis application is the diverse nature of their data. This specific statistic nature also limits the ability to provide considerable multifaceted data integration.

Furthermore, no appropriate feature descriptors for the most modern sensors, i.e., RGBD sensors, are available. These barriers are clear in the pertinent composition and are discussed in the article. The computational recognition methods available in the literature are insufficient for dealing with dynamic-feature hyperdimensional data for categorization. Citrus fruits are divided into several categories, each with a unique set of characteristics. The identified classification techniques are limited by the absence of large datasets. The majority of the investigations in the review are restricted about categories or size of the dataset. A step towards making it possible to provide off-the-shelf modules for computer sensing systems is being done to build pre-trained CNN. Nevertheless, as these pre-trained CNN are data-dependent, it is difficult to get a dataset with a sizable amount of citrus fruits.

The authors encountered a variety of issues as they worked on classifying the diseases in food products. The main issue is the lack of a consistent database with information on specific diseases and crops. The academics are discouraged from working on this area of research due to the database's lack of availability. The issue with database generation comes afterward. The process of collecting real-time data from the field under various environmental factors is highly difficult and exhausting.

Real-time images have a lot of invariables such as distinct textures, distinct background features, image-taking angles, etc., which adds to the problem of preprocessing the image. Another concomitant issue with this is the choice of collecting devices. The choice of the actual field area for picture acquisition, the choice of the plant, the choice of the disease component of the plant, and the choice of the disease are some of the other issues. Another issue the author must address is the choice of illness and its manifestations that distinguish it from others in a particular way.

The selection of a design strategy that will result in a system that performs better while taking up less time and money is another consideration.

Future applications can be suggested to develop a real-time system that assists with decisions for improving crop productivity as well as quality. Among them include the use of equipment like drones, sensors, and superior cameras; establishing internet-based crop management systems; using hyperspectral or remote sensing images to measure crop efficiency, implementing internet of things technologies in plant pathology; and collaborating with artificial intelligence, cloud computing, IoT, edge computing and machine learning algorithms, among other things.

5. Conclusion:

This study provides a comparative analysis of several constraints of the citrus fruit detection system and cutting-edge computer vision methods utilized for categorization. Numerous image processing approches are discussed in this survey for the citrus fruit detecting system. Preprocessing, segmentation, feature extraction, and classification are the four key phases in this survey. Each phase is contrasted in terms of technique, effectiveness, benefits, and drawbacks. We conclude that pre-processing techniques improve segmentation accuracy. We also get the conclusion that graphic enhancement/filtering and thresholding are the two most used image processing approaches. Additionally, SVM and NN make use of the texture features, which are especially notable for depicting disease in the citrus fruit image.

There has been a rigorous analysis of the classification procedure offered. The overview of a systematic study takes into account major sensor amenities, feature specifications, and classification techniques. To understand the present crucial issues in this sector, a comparison of classification techniques is made. To collect data for various applications in the food sector, the study investigates the considerable limitations of using currently accessible sensors and the amalgamation of several sensors. The report also discusses briefly the challenges of multi-sensory data fusion. The significance of pre-processing and segmentation needed for computer vision-based investigation in the food business has been raised.

References

[1] C. Jackulin and S. Murugavalli, "A comprehensive review on detection of plant disease using machine learning and deep learning approaches," *Measurement: Sensors*, pp. 100 441–100 441, 2022.

[2] C. Simon, A. Mansouri, F. S. Marzani, and F. Boochs, "Integration of 3D and multispectral data for cultural heritage applications : Survey and perspectives ☆," *Image Vis. Comput*, vol. 31, no. 1, pp. 91–102, 2012.

[3] R. Pydipati, T. F. Burks, and W. S. Lee, "Statistical and neural network classifiers for citrus disease detection using machine vision," *Trans. ASAE*, vol. 48, no. 5, pp. 2007–2014, 2014.

[4] D. M. Bulanon, T. F. Burks, and V. Alchanatis, "Image fusion of visible and thermal images for fruit detection," *Biosyst. Eng*, vol. 103, no. 1, pp. 12–22, 2009.

[5] C. Malegori, "Talanta Comparing the analytical performances of Micro-NIR and FT-NIR spectrometers in the evaluation of acerola fruit quality , using PLS and SVM regression algorithms," *Talanta*, vol. 165, pp. 112–116, 2016.

[6] B. Doh, D. Zhang, Y. Shen, F. Hussain, R. F. Doh, and K. Ayepah, "Automatic citrus fruit disease detection by phenotyping using machine learning," *25th IEEE International Conference on Automation and Computing*, pp. 1–5, 2019.

[7] D. Lorente, P. Escandell-Montero, S. Cubero, J. Gómez-Sanchis, and J. Blasco, "Visible-NIR reflectance spectroscopy and manifold learning methods applied to the detection of fungal infections on citrus fruit," *J. Food Eng*, vol. 163, pp. 17–24, 2015.

[8] J. Gómez-Sanchis, J. D. Martín-Guerrero, E. Soria-Olivas, M. Martínez-Sober, R. Magdalena-Benedito, and J. Blasco, "Detecting rottenness caused by Penicillium genus fungi in citrus fruits using machine learning techniques," *Expert Syst. Appl*, vol. 39, no. 1, pp. 780–785, 2012.

[9] K. Itakura, Y. Saito, T. Suzuki, N. Kondo, and F. Hosoi, *Estimation of citrus maturity with fluorescence spectroscopy using deep learning*, vol. 5, pp. 1–9, 2019.

[10] K. Vijayarekha and R. Govindaraj, *Citrus fruit external defect classification using wavelet packet transform features and ANN*, pp. 2872–2877, 2006.

[11] K. Tarale and A. Bavaskar, "Fruit Detection Using Morphological Image Processing Technique," *International Conference on Science and Engineering for Sustainable Development*, pp. 60–64, 2017.

[12] D. Sahu and C. Dewangan, "Identification and Classification of Mango Fruits Using Image Processing," *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol*, vol. 2, no. 2, pp. 203–210, 2017.

[13] F. Dadrasjavan, F. Samadzadegan, S. H. S. Pourazar, and H. Fazeli, "UAV-based multispectral imagery for fast Citrus Greening detection," *J. Plant Dis. Prot*, vol. 126, no. 4, pp. 307–318, 2019.

[14] X. L. Deng, Y. Lan, X. Q. Xing, H. L. Mei, J. K. Liu, and T. S. Hong, "Detection of citrus huanglongbing based on image feature extraction and two-stage BPNN modeling," *Int. J. Agric. Biol. Eng*, vol. 9, no. 6, pp. 20–26, 2016.

[15] M. Svedlow, C. D. Mcgillem, and P. E. Anuta, "Image Registration: Similarity Measure and Preprocessing Method Comparisons," *IEEE Trans. Aerosp. Electron. Syst*, vol. 14, no. 1, pp. 141–150, 1978.

[16] J. D. Pujari and R. Yakkundimath, "Grading and Classification of Anthracnose Fungal Disease of Fruits based on Statistical Texture Features," *Citeseer*, vol. 52, pp. 121–132, 2013.

[17] S. H. Ong, N. C. Yeo, K. H. Lee, Y. V. Venkatesh, and D. M. Cao, "Segmentation of color images using a two-stage self-organizing network," *Image Vis. Comput*, vol. 20, no. 4, pp. 279–289, 2002.

[18] H. Ali, M. I. Lali, M. Z. Nawaz, M. Sharif, and B. A. Saleem, "Symptom based automated detection of citrus diseases using color histogram and textural descriptors," *Comput. Electron. Agric*, vol. 138, pp. 92–104, 2017.

[19] C. Zheng, D. W. Sun, and L. Zheng, "Recent developments and applications of image features for food quality evaluation and inspection - a review," *Trends Food Sci. Technol*, vol. 17, no. 12, pp. 642–655, 2006.

[20] A. Bhargava and A. Bansal, "Fruits and vegetables quality evaluation using computer vision: A review," *J. King Saud Univ. - Comput. Inf. Sci*, 2018.

[21] A. Pourreza, W. S. Lee, M. A. Ritenour, and P. Roberts, "Spectral characteristics of citrus black spot."

[22] M. M and S. A. Papert, "Perceptrons: An introduction to computational geometry," 2017.

[23] G. Grekousis, "Artificial neural networks and deep learning in urban geography: A systematic review and meta-analysis," *Comput. Environ. Urban Syst*, vol. 74, pp. 244–256, 2019.

[24] K. Hornik, "Approximation Capabilities of Muitilayer Feedforward Networks," *Neural networks*, vol. 4, pp. 251–257, 1989.

[25] A. Shrestha and A. Mahmood, "Review of deep learning algorithms and architectures," *IEEE Access*, vol. 7, pp. 53 040–53 065, 2019.

[26] C. T. Soini and M. R. Abid, "Citrus Greening Infection Detection (CiGID) by Computer Vision and Deep Learning," *proceeding of 3rd International Conference on Information System and Data Mining*, pp. 21–26,

2019.
[27] M. S. H and P. C. J, “Automatic Detection of Surface Defects on Citrus Fruit based on Computer Vision Techniques,” *Int. J. Image, Graph. Signal Process*, vol. 7, no. 9, pp. 11–19, 2015.
[28] M. V. Dael, “A segmentation and classification algorithm for online detection of internal disorders in citrus using X-ray radiographs,” *Postharvest Biol. Technol*, vol. 112, pp. 205–214, 2016.
[29] S. K. Behera, L. Jena, A. K. Rath, and P. K. Sethy, “Disease Classification and Grading of Orange Using Machine Learning and Fuzzy Logic,” *Proceedings of the 2018 IEEE International Conference on Communication and Signal Processing*, pp. 678–682, 2018.
[30] S. A. Khoje, S. K. Bodhe, and A. Adsul, “Automated Skin Defect Identification System for Fruit Grading Based on Discrete Curvelet Transform,” *Int. J. Eng. Technol*, vol. 5, no. 4, pp. 3251–3256, 2013.
[31] R. Saha, “Orange Fruit Disease Classification using Deep Learning Approach,” *Int. J. Adv. Trends Comput. Sci. Eng*, vol. 9, no. 2, pp. 2297–2301, 2020.
[32] P. Theanjumpol, K. Wongzeewasakun, and N. Muenmanee, “Non-destructive identification and estimation of granulation in ‘ Sai Num Pung ’ tangerine fruit using near infrared spectroscopy and chemometrics,” *Postharvest Biol. Technol*, vol. 153, pp. 13–20, 2019.
[33] R. Thendral and A. Suhasini, “Automated skin defect identification system for orange fruit grading based on genetic algorithm,” *Curr. Sci*, vol. 112, no. 8, pp. 1704–1711, 2017.
[34] A. M. Khan and A. P. Paplinski, “Blemish detection in citrus fruits,” *proceeding of SPIT-IEEE Colloquium and International Conference*, vol. 1, pp. 262–271, 2008.
[35] J. Jhawar, “Orange Sorting by Applying Pattern Recognition on Colour Image,” *Praocedia Computer Science*, vol. 78, pp. 691–697, 2015.
[36] M. Kaur and R. Sharma, “Quality Detection of Fruits by Using ANN Technique,” *IOSR J. Electron. Commun. Eng. Ver. II*, vol. 10, no. 4, pp. 2278–2834, 2015.
[37] W. M. Miller, “Optical defect analysis of Florida citrus,” *Appl. Eng. Agric*, vol. 11, no. 6, pp. 855–860, 1995.
[38] V. Kavitha and M. R. Devi, “Predicting the Diseases by Graphcut Method for Citrus Fruits,” *Int. Res. J. Manag. Sci. Technol*, vol. 7, no. 12, pp. 465–470, 2016.
[39] M. Sharif, M. A. Khan, Z. Iqbal, M. F. Azam, M. I. U. Lali, and M. Y. Javed, “Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection,” *Comput. Electron. Agric*, vol. 150, pp. 220–234, 2017.
[40] G. Capizzi, G. Lo, C. Sciuto, E. Napoli, M. Tramontana, and Wozniak, “Automatic classification of fruit defects based on Co-occurrence matrix and neural networks,” *Proceedings of Federated Conference on Computer Science and Information Systems*, pp. 861–867, 2015.
[41] K. N. Ranjit, K. S. Raghunandan, C. Naveen, H. K. Chethan, and C. Sunil, “Deep Features Based Approach for Fruit Disease Detection and Classification,” *Int. J. Comput. Sci. Eng*, vol. 7, no. 4, pp. 2347–2693, 2019.
[42] S. Qiu, J. Wang, C. Tang, and D. Du, “Comparison of ELM, RF, and SVM on E-nose and E-tongue to trace the quality status of mandarin (Citrus unshiu Marc,” *J. Food Eng*, vol. 166, pp. 193–203, 2015.
[43] D. Lorente, N. Aleixos, J. Gómez-Sanchis, S. Cubero, and J. Blasco, “Selection of Optimal Wavelength Features for Decay Detection in Citrus Fruit Using the ROC Curve and Neural Networks,” *Food Bioprocess Technol*, vol. 6, no. 2, pp. 530–541, 2011.
[44] D. M. Bulanon, T. F. Burks, D. G. Kim, and M. A. Ritenour, “Citrus black spot detection using hyperspectral image analysis,” *Agric Eng Int CIGR J. Open*, vol. 15, no. 3, pp. 171–180, 2013.
[45] D. G. Kim, T. F. Burks, J. Qin, and D. M. Bulanon, “Classification of grapefruit peel diseases using color texture feature analysis,” *Int. J. Agric. Biol. Eng*, vol. 2, no. 3, pp. 41–50, 2009.
[46] Y. Zhang, W. S. Lee, M. Li, L. Zheng, and M. A. Ritenour, “Non-destructive recognition and classification of citrus fruit blemishes based on ant colony optimized spectral information,” *Postharvest Biol. Technol*, vol. 143, pp. 119–128, 2018.
[47] A. Bhargava and A. Bansal, “Automatic Detection and Grading of Multiple Fruits by Machine Learning,” *Food Anal. Methods*, vol. 13, no. 3, pp. 751–761, 2019.
[48] D. Choi, W. S. Lee, J. K. Schueller, R. Ehsani, F. Roka, and J. Diamond, “A performance comparison of RGB, NIR, and depth images in immature citrus detection using deep learning algorithms for yield prediction,” *Annual International Meeting*, pp. 1–6, 2017.
[49] C. Senthilkumar and M. Kamarasan, “An Effective Classification of Citrus Fruits Diseases using Adaptive Gamma Correction with Deep Learning Model,” *Int. J. Eng. Adv. Technol*, vol. 9, no. 2, pp. 2249–8958, 2020.
[50] S. Moomkesh, S. Ahmad, and M. Sadeghi, “ScienceDirect Early detection of freezing damage in sweet lemons using Vis / SWNIR spectroscopy,” *Biosyst. Eng*, vol. 164, no. 31, pp. 157–170, 2017.
[51] X. Xie, “Image matching algorithm of defects on navel orange surface based on compressed sensing,” *J. Ambient Intell. Humaniz. Comput*, vol. 0, no. 0, pp. 1–9, 2018.
[52] G. Capizzi, G. Lo, C. Sciuto, E. Napoli, M. Tramontana, and Woźniak, “A novel neural networks-based texture image processing algorithm for orange defects classification,” *Int. J. Comput. Sci. Appl*, vol. 13, no. 2, pp. 45–60, 2016.
[53] G. Kim, K. Lee, K. Choi, J. Son, D. Choi, and S. Kang, “Defect and ripeness inspection of citrus using NIR transmission spectrum,” *Key Eng. Mater*, no. II, pp. 1008–1013, 2004.
[54] J. Gómez-Sanchis, “Hyperspectral system for early de-

tection of rottenness caused by Penicillium digitatum in mandarins," *J. Food Eng*, vol. 89, no. 1, pp. 80–86, 2008.

[55] G. Stegmayer, D. H. Milone, S. Garran, and L. Burdyn, "Automatic recognition of quarantine citrus diseases," *Expert Syst. Appl*, vol. 40, no. 9, pp. 3512–3517, 2013.

[56] A. Wajid, N. K. Singh, P. Junjun, and M. A, "Recognition of ripe, unripe and scaled condition of orange citrus based on decision tree classification," *proceeding of international confrence on computing,mathematics and engineering technologies*, pp. 1–4, 2018.

[57] W. Pan, J. Qin, X. Xiang, Y. Wu, Y. Tan, and L. Xiang, "A Smart Mobile Diagnosis System for Citrus Diseases Based on Densely Connected Convolutional Networks," *IEEE Access*, vol. 7, pp. 87 534–87 542, 2019.

[58] J. Qin, T. F. Burks, M. S. Kim, K. Chao, and M. A. Ritenour, "Citrus canker detection using hyperspectral reflectance imaging and PCA-based image classification method," *Sens. Instrum. Food Qual. Saf*, vol. 2, no. 3, pp. 168–177, 2008.

[59] A. Rahmanian, S. A. Mireei, S. Sadri, M. Gholami, and M. Nazeri, "Application of biospeckle laser imaging for early detection of chilling and freezing disorders in orange," *Postharvest Biol. Technol*, vol. 162, pp. 111 118–111 118, 2020.

[60] W. M. Miller and G. P. Drouillard, "Multiple feature analysis for machine vision grading of Florida citrus," *Appl. Eng. Agric*, vol. 17, no. 5, pp. 627–633, 2001.

[61] D. Zhu, L. Xie, B. Chen, J. Tan, R. Deng, Y. Zheng, . . Andrew, and W. H, *Knowledge graph and deep learning based pest detection and identification system for fruit quality*, pp. 100 649–100 649, 2023.

[62] A. Jahanbakhshi, M. Momeny, M. Mahmoudi, and Y. D. Zhang, "Classification of sour lemons based on apparent defects using stochastic pooling mechanism in deep convolutional neural networks," " *Sci. Hortic. (Amsterdam)*, vol. 263, 2020.

[63] G. L. Yang, L. Luo, Y. Q. Feng, and H. S. Zhao, "Research of navel orange defect and color detection based on machine vision," *Appl. Mech. Mater*, vol. 513, pp. 3442–3445, 2014.

[64] J. M. Cevallos-Cevallos, D. B. Futch, T. Shilts, S. Y. Folimonova, and J. I. Reyes-De-Corcuera, "GC-MS metabolomic differentiation of selected citrus varieties with different sensitivity to citrus huanglongbing," *Plant Physiol. Biochem*, vol. 53, pp. 69–76, 2012.

[65] J. J. Lopez, E. Aguilera, and M. Cobos, "Defect detection and classification in citrus using computer vision," *proceeding International Conference on Neural Information Processing*, pp. 11–18, 2009.

[66] J. P. Mercol, J. Gambini, and J. M. Santos, "Automatic classification of oranges using image processing and data mining techniques," in XIV Congreso Argentino de Ciencias de la Computación," 2008.

[67] L. S. Magwaza, "The use of Vis/NIRS and chemometric analysis to predict fruit defects and postharvest behaviour of 'Nules Clementine' mandarin fruit," *Food Chem*, vol. 163, pp. 267–274, 2014.

[68] G. Kumar and Y. S. Suhas, "Identification and Classification of Fruit Diseases," *International Conference on Recent Trends in Image Processing and Pattern Recognition*, pp. 382–390, 2016.

[69] C. Dong, Y. Ye, J. Zhang, H. Zhu, and F. Liu, "Detection of Thrips Defect on Green-Peel Citrus Using Hyperspectral Imaging Technology Combining PCA and B-Spline Lighting Correction Method," *J. Integr. Agric*, vol. 13, no. 10, pp. 60 671–60 672, 2014.

[70] V. H. Pham and B. R. Lee, "An image segmentation approach for fruit defect detection using k-means clustering and graph-based algorithm," *Vietnam J. Comput. Sci*, vol. 2, no. 1, pp. 25–33, 2015.

[71] Y. Chen, J. Wu, and M. Cui, "Automatic classification and detection of oranges based on computer vision," *procceding of 4th International Conference on Computer and Communications*, pp. 1551–1556, 2018.

[72] J. Abdulridha, O. Batuman, and Y. Ampatzidis, "UAV-based remote sensing technique to detect citrus canker disease utilizing hyperspectral imaging and machine learning," *Remote Sens*, vol. 11, pp. 1373–1373, 2019.

[73] L. Huijun and W. Xiangfeng, "Rapid shelf-life identification model of citrus based on near infrared spectroscopy," *Proceedings of International Symposium on Knowledge Acquisition and Modeling*, pp. 298–301, 2008.

[74] D. Lorente, M. Zude, C. Regen, L. Palou, J. Gómez-Sanchis, and J. Blasco, "Early decay detection in citrus fruit using laser-light backscattering imaging," *Postharvest Biol. Technol*, vol. 86, pp. 424–430, 2013.

[75] C. J. Enciso-Aragón and R. Jimenez-Moreno, "Quality control system by means of CNN and fuzzy systems," *Int. J. Appl. Eng. Res*, vol. 13, no. 16, pp. 12 846–12 853, 2018.

[76] E. G. Turitsyna and S. Webb, "Hyperspectral detection of citrus damage with Mahalanobis kernel classifier," *Electron. Lett*, vol. 41, no. 2, pp. 40–41, 2005.

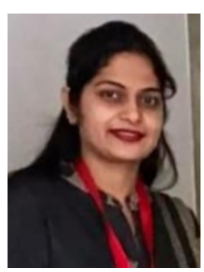
[77] F. López-García, G. Andreu-García, J. Blasco, N. Aleixos, and J. M. Valiente, "Automatic detection of skin defects in citrus fruits using a multivariate image analysis approach," *Comput. Electron. Agric*, vol. 71, no. 2, pp. 189–197, 2010.

[78] S. Taghadomi-Saberi, A. A. Masoumi, M. Sadeghi, and M. Zekri, "Integration of wavelet network and image processing for determination of total pigments in bitter orange (Citrus aurantium L.) peel during ripening," *J. Food Process Eng*, vol. 42, no. 5, pp. 1–8, 2019.

[79] & F Steinmetz, V. Biavati, E. Molto, E. Pons, and R, "Predicting the maturity of oranges with non destructive sensors," *international Symposium On Sensors in Horticulture*, vol. 421, pp. 271–278, 1995.

[80] H. Patel, R. Prajapati, and M. Patel, "Detection of Quality in Orange Fruit Image using SVM Classifier," *3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, pp. 74–78, 2019.

[81] T. Wen, "Rapid detection and classification of citrus fruits infestation by Bactrocera dorsalis (Hendel) based on electronic nose," *Postharvest Biol. Technol*, vol. 147, pp. 156–165, 2018.
[82] Y. Ashwani, K. Dubey, R. Ratan, and A. Rocha, "Computer vision based analysis and detection of defects in fruits causes due to nutrients deficiency," *Cluster Comput*, vol. 6, pp. 10 586–10 605, 2019.
[83] H. Singh and N. Gill, "Machine Vision Based Color Grading of Kinnow Mandarin," *Int. J. Adv. Res. Comput. Sci. Softw. Eng*, vol. 5, no. 5, pp. 1253–1259, 2015.
[84] S. Cubero, J. Blasco, S. Cubero, J. Blasco, and A. Ferrer, "VIS/NIR hyperspectral imaging and N-way PLS-DA models for detection of decay lesions in citrus fruits," *Chemom. Intell. Lab. Syst*, vol. 156, pp. 241–248, 2016.
[85] P. K. S. S. Kumari and Behera, "Automatic Fruits Identification and Disease Analysis using Machine Learning Techniques," *Int. J. Innov. Tecchnology Explor. Eng*, vol. 8, no. 6S2, pp. 103–107, 2019.
[86] M. A. Gawande and S. S. Dhande, "Implementation of Fruits Grading and Sorting System by using Image Processing and Data Classifier," *SSRG Int. J. Comput. Sci. Eng*, vol. 2, no. 6, pp. 22–27, 2015.
[87] A. Kamalakannan and G. Rajamanickam, "Surface defect detection and classification in mandarin fruits using fuzzy image thresholding, binary wavelet transform and linear classifier model," *proceeding of4th International Conference on Advanced Computing*, pp. 1–6, 2012.
[88] B. O. Fiona, M. R. Thomas, S. Maria, and I. J. Hannah, "Identification Of Ripe And Unripe Citrus Fruits Using Artificial Neural Network," *Journal of Physics: Conference Series*, vol. 1362, pp. 12 033–12 033, 2019.
[89] Y. Lan, "Comparison of machine learning methods for citrus greening detection on UAV multispectral images," *Comput. Electron. Agric*, vol. 171, pp. 105 234–105 234, 2020.
[90] R. Hadipour-Rokni, E. A. Asli-Ardeh, A. Jahanbakhshi, and S. Sabzi, "Intelligent detection of citrus fruit pests using machine vision system and convolutional neural network through transfer learning technique," *Computers in Biology and Medicine*, vol. 155, pp. 106 611–106 611, 2023.
[91] M. Momeny, A. Jahanbakhshi, A. A. Neshat, R. Hadipour-Rokni, Y. D. Zhang, and Y. Ampatzidis, "Detection of citrus black spot disease and ripeness level in orange fruit using learning-to-augment incorporated deep networks," *Ecological Informatics*, pp. 101 829–101 829, 2022.
[92] S. K. Behera, L. Jena, A. K. Rath, and P. K. Sethy, "Disease Classification and Grading of Orange Using Machine Learning and Fuzzy Logic," *Proceedings of IEEE International Conference on Communication and Signal Processing*, pp. 678–682, 2018.
[93] N. Henderson, R. King, and S. K. Chalup, "An Automated Colour Calibration System using Multivariate Gaussian Mixtures to Segment HSI Colour Space."
[94] H. Palus, "Representations of colour images in different colour spaces," *The Colour image processing handbook*, pp. 67–90, 1998.
[95] D. Rong, X. Rao, and Y. Ying, "Computer vision detection of surface defect on oranges by means of a sliding comparison window local segmentation algorithm," *Comput. Electron. Agric*, vol. 137, pp. 59–68, 2017.
[96] D. Cooper, L. Doucet, and M. Pratt, "Detection and classification of citrus green mold caused by Penicillium digitatum using multispectral imaging," *J. Sci. Food Agric*, vol. 98, no. 0, pp. 3542–3550, 2018.
[97] Y. Zhang, "Navel Orange Pest Image Recognition Based on Convolution Deep Neural Network," *Int. J. Simulation–Systems, Sci. Technol*, vol. 17, no. 42, pp. 8–12, 2008.
[98] J. J. Lopez, M. Cobos, and E. Aguilera, "Computer-based detection and classification of flaws in citrus fruits," *Neural Comput. Appl*, vol. 20, no. 7, pp. 975–981, 2011.



Dr. Poonam Dhiman is currently working as an assistant professor at Government PG College Ambala cant, Haryana, India. Dr. Dhiman has attained her doctorate degree from chitkara university institude of engineering and technology, CU Punjab. She has done her M.tech degree with distinction from Delhi Technological University formerly known as Delhi College of Engineering, Delhi. She has done her B.Tech from Chandigarh College of Engineering and Technology; Punjab University. She has many Publications in renowned SCIE, SCOPUS International journals and fully refereed International conferences with experience of 9 years. She has filed and published patents also. Main areas of research are software engineering, machine learning, IoT and deep learning.

Dr. Amandeep kaur is currently working as a professor at chitkara university institude of engineering and technology, CU Punjab.Dr. kaur has attained her doctorate degree from I.K. GUJRAL Panjab technical University, Jalandhar. Her both M.Tech(CSE) and B.tech(CSE) degrees are with distinction. She has about 100 Publications in renowned International journals and fully refereed International conferences with experience of 23 years. She has filed and published more than 80 patents. She has supervised more than 35 Ph.D. and PG students. Main areas of research are medical Informatics, machine learning, IoT and cloud computing.

Vinay kukreja is working as an professor (CSE) , Chitkara University, Punjab, India. He has total experience of 16 years and has guided many ME Scholars and PhD Scholars. He has having many research papers of SCIE, SCOPUS and PEER reviewed journals to his name. He has also authored many international books and granted many patents. His research areas are Machine learning, Deep Learning, NLP and agile software development.