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Systematic Literature Review Approach on the Fruit Quality Assessment Based on Fruit Imaging Techniques

Iylia Adhwa Mazni*, Samsul Setumin, Mohamed Syazwan Osman, Khusairi Osman, and Mohd Subri Tahir

Abstract— **Non-destructive quality assessment is one of the methods in image processing used to evaluate the qualities of fruits without destroying the internal structure and external appearance. Imaging processing techniques and machine learning methods have emerged as an effective way to evaluate fruit quality assessment, which helps to classify the fruit's quality, especially during the harvest process. Image processing significantly shifts in fields, especially agriculture, medical, marketing profiling and vehicles. The rapid progress in agriculture continually increases the demand for up-to-date and accurate data to characterise the modality of imaging techniques used to evaluate the quality of fruits, which helps to guide and support research decisions, especially for future researchers that are new. This systematic literature review will focus on the type of fruits, type of modalities, pre-processing of imaging techniques and classification experiments that had been studied in recent years using planning, conducting and reporting methods. Through this study, 486 papers were selected at a preliminary stage and narrowed down to 35 papers that had been investigated from specialised research that has indicated the preferential types of data and regions of interest in image processing. In addition, imaging technique papers published between 2016 to 2022 have been studied, discussed and analysed. The presented finding outlines important research determination whose regardful report is of great value to this research community.**

Index Terms—**Fruits, Imaging techniques, Quality assessment.**

I. INTRODUCTION

TODAY, high-quality fruits are highly demanded as humans nowadays are very particular about health and the quality of the fruits, which is becoming a concern for suppliers, especially in harvest processing. Quality of external and internal evaluation toward fruits are generally used as a destructive method while the rest are based on the physical appearance such as a defect that can be seen through the skin and optical appearance [1]. In the past, fruits were sorted manually, which mostly depended on human labour and was time-consuming [2]. This could be the cause to create an automatic quality assessment of fruits using image processing and machine learning.

Subjective judgment by a human that depends on four senses like taste, smell, hearing, and sight is the norm for fruit evaluation. However, this conventional method mostly provides misleading and inaccurate about the condition of the fruits [3]. Image processing and machine learning are the trends to overcome the problem. Still, most of the previously published papers only focus on a single modality with less inaccuracy, efficiency in the result and data collection [4]. This problem makes it important to obtain multiple quality information, multi-modality or multi-technologies [4]. To get the higher precision data, high-end equipment was normally used, but the cost would be extremely high, limiting the use of equipment to monitor the quality of fruits [3]. This led to an idea to combine several modalities and technologies to increase accuracy, efficiency and at the same time, it can reduce cost. Various applications of image processing in the field of agriculture like identification of land [5], evaluation of nitrogen recognition fruit [6], recognition of infected areas [7], automatic classification and detection of fruits disease from shape, texture and colour [8].

As science and technology information becomes more advanced, image processing has grown as a technique that accesses the safety and quality of fruits. Various agriculture applications were working electronically like sensing the image, interpreting and recognising the image of the fruits [9]. As a result, various papers were published to investigate fruit quality using image processing according to each researcher's interest [9].

Systematic Literature Review (SLR) was conducted in this study with systematic ways to provide a scope of a research paper according to the corresponding experiment area. A comparable review of the image processing techniques will be done in this paper where several stages will be discussed to investigate the quality of fruits. The principal component, basic theory and basic analysis according to the extraction paper followed by selection criteria are reported.

II. SYSTEMATIC LITERATURE REVIEW PROCESS

This SLR is based on the proposed guidelines [10], with modifications where the systematic technique allows for collecting

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Iylia Adhwa Mazni, Samsul Setumin, Mohamed Syazwan Osman, Khusairi Osman and Mohd Subri Tahir are with Universiti Teknologi MARA, Cawangan Pulau Pinang, Permatang Pauh, 13500 Pulau Pinang, Malaysia

*Corresponding author
Email address: iyliaadhwa@gmail.com

the data and summary of scientific evidence from primary investigations in a uniform manner. As a result, SLR is a study that varies from other researchers and systematises the entire review process, reducing researcher bias and resulting in conclusions specific to the scope needed. The actions are done in each phase of the systematic review approach, including planning, conducting, and reporting as depicted in Figure 1. This section summarises the actions carried out during the planning and execution phases.

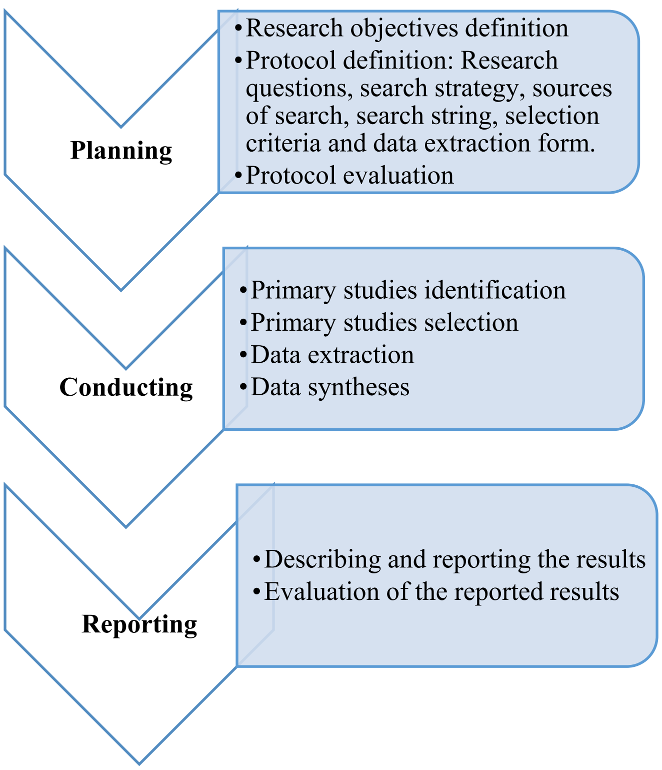

Figure 1: SLR stages

A. *Research objective*

The objective of the SLR reported in this paper is to investigate the method used for quality assessment of the fruits using imaging techniques developed from 2016 to 2022. In addition to that, frequent type of fruits that have been reported is also being analysed. The major aspects such as modalities, pre-processing, and classification experiments related to image processing had been emphasised. Those aspects are linked with the research questions guide as discussed in the following section.

B. *Research question*

To answer the research objective, the research questions below signify the guideline for this review paper:

RQ1: What type of fruits had been investigated frequently?
RQ2: What are the common imaging modalities used to investigate the quality assessment of the fruits with their advantage and disadvantage?
RQ3: Which pre-processing techniques have been employed in the proposed assessment methods of the fruits?
RQ4: Which classification method was used to classify the fruit to investigate the quality of the fruits?

C. *Search process*

The search process will show how the papers were found and selected through two strategies, as shown in Figure 2: an automated search in four main databases and a manual search outside the standard search process. This allowed the references to be established within the scope of the study.

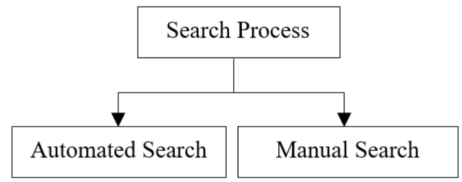

Figure 2: Two strategies of the search process.

1. Automated search

The Scopus, Science Direct, IEEE Xplore and Web of Science (WoS) databases were chosen as well-known and had a reputed database that helps query important journals and conferences proceeding in the area of technology and science with the basics of the author's analysis of preliminary results. Although Scopus and WoS have differences in terms of index studies in certain criteria that come from many databases, identical papers are expected from multiple databases, and several unique documents that ensure diversity are intended to contribute to each database. To find the paper that is relevant to the topic in more detail, the following basic search string based on the terms identified in the research questions and their synonyms has been developed, which can be further adapted to each search tool. Here is the example: **TITLE:** ("non-destructive") AND (fruit OR fruits) AND **TITLE OR ABSTRACT OR KEYWORDS:** ("quality evaluation" OR "quality assessment" OR quality) AND ("imaging" OR "imaging technique" OR "image processing"). The search was conducted in August 2022 and was limited to studies around seven years back that were published between 2016 to 2022, including materials that were accessible as "early access" in the databases and the language was limited to English only.

2. Manual Search

Manual searches were conducted by searching the topic related to "Quality assessment of the fruits" or "imaging technique". Whereas a large number of primary studies are expected to be retrieved from bibliographic databases by automatic searches, the manual search is meant to be complementary and allow researchers to consider possibly relevant studies that were not found using a specific search string and also some papers [11] that were not under four databases that have been mention earlier.

D. *Selection criteria*

Following the automated and manual searches, all the relevant documents are extracted from the database and performed in two stages: the preliminary and final selection. The goal of the preliminary selection is to decrease the number of documents that must be read in whole by evaluating only specified parts of all documents first and then reviewing the complete text of the accepted or filtered paper according to certain criteria. Two criteria were selected to ensure reliability in this process: the inclusion and exclusion criteria described in Table 1.

TABLE I
INCLUSION AND EXCLUSION CRITERIA.

Inclusion criteria	
IC01	Study recent imaging techniques to evaluate the quality of the fruits.
IC02	Study the modalities and methods used to analyse the internal and external quality of the fruits.
Exclusion criteria	
EC01	Study is not available in full text.
EC02	Study is not available in English.
EC03	Study was not published between 2016 and 2022.
EC04	Study is a redundant paper.
EC05	Study does not mention the quality evaluation for internal or external fruits.
EC06	Study approaches related to imaging technique only but does not state the imaging modalities used.
EC07	Study results only focus on chemical properties without considering the imaging technique and ML method.
EC08	Study only considers “fruit” as a general discussion.
EC09	Study does not yield a favourable outcome according to the modalities used.
EC10	Study does not present either IC01 AND IC02
EC11	Study is a course description, lecture note, patent, editorial, tutorial, survey, or review paper.

There are two inclusion criteria, practically divided into categories in which we acknowledge works that propose an imaging technique for internal and external quality such as sugar level, stage of ripening, and moisture content. This work describes a method where modalities and machine learning are used in practice. The exclusion criteria define some characteristics of a paper that make it out of scope for this assessment whether it meets any of the inclusion criteria stated in EC10. Additional exclusion criteria can clarify the reasons for exclusion because a document under evaluation can have several selection criteria. For example, EC05 shows a document that might focus on sorting the fruits according to the fruit's physical appearance without evaluating the internal quality. As fruits had been discussed in this paper, the experiment classification needs to involve modalities and machine learning as stated in EC07 including the techniques and method used. The common exclusion stated in EC01, EC02, EC03 and EC04 become the first criteria to be considered before going deep into the objective of the studies.

A document is approved if no exclusion criteria are met. Besides, an exclusion criterion is only applied to a document if it can be verified. If there is a doubt, work is always accepted and subject to a more thorough review in the next selection phase.

E. Data extraction form.

A data extraction form was developed and will be discussed, including the review after the selection processes to collect evidence to address the research questions stated in section B (research question). The research questions also aided in collecting the data gathered from the studies. The data were grouped into six sections as presented in Table 2 below: (1) Metadata, (2) Types of fruits, (3) Imaging modalities, (4) Pre-processing, (5) Classification experiment and (6) Results.

TABLE II
DATA EXTRACTION FORM WITH DESCRIPTION.

Extracted data	Description
1. Metadata	Title, author and publication year of the study.
2. Type of fruits	The type of fruit used as an experiment material in the studies.
3. Imaging modalities	Techniques or tools have been used to evaluate the quality of the fruits. (Example: backscattering, MRI, NIR spectroscopy, HSI, MSI, etc.). The outcome or result comes from each modality used. (Example: Image, hyperspectral, multispectral, etc.).
4. Pre-processing	
4.1. Feature extraction	-A process of the raw data into numerical features (Example: colour and texture)
4.2. Enhancement	-The step used to improve the image quality (Example: blurring, sizing, etc.).
4.3. Segmentation	-Example: cropping, background improvement
5. Classification experiments	
5.1. Data sample	-The subset employed (Example: number of subjects or database)
5.2. Classification using machine learning	-Stated the use of machine learning in the studies.
6. Results	

F. Protocol evaluation

The protocol evaluation was assessed in two areas: the definition of the search string used to query each database and the definition of the selection criteria, as discussed in section D (selection criteria). Some resources can combine queries where every database works differently. Because of these factors, modified search strings differ from generic ones, which may impact the predicted results. As a result, experimental searches and selections were conducted to see if the general search string adaptations produced acceptable results. Before the conducting phase, the search string was refined, and several selection criteria were adjusted for clarity and completeness. This protocol is applied to each search tool and database manually or automatically.

G. Search and selection result

In this section, there are three main stages as illustrated in Figure 3: duplicate removal, preliminary selection, and final selection. In the duplicate removal stage, duplicates are expected to be obtained. For example, the database in Scopus has a duplicate document in Science Direct, meaning one paper exists in two databases. After removing duplicates, there were 486 documents left, considering the initial set of selected documents to be considered in this review. Only the title and abstract of the 486 selected documents in the original set were reviewed during the preliminary selection stage. In this section, four indexers such as IEEE, Scopus, Science Direct, WoS and additional manual search assessed each document's suitability for the previously specified inclusion and exclusion criteria as summarised in Table 1. As a result, 123 documents were evaluated for further investigation from 363 documents that are being filtered.

Lastly, the final selection stage undergoes the full-text reading of the documents selected in the preliminary selection to see whether the paper's context is relevant considering this study's objective. As a result, documents were kept in this review, which equates to 28.5% of the evaluated 35 documents in this phase and 7.2% of the initial set documents had been retrieved from this process.

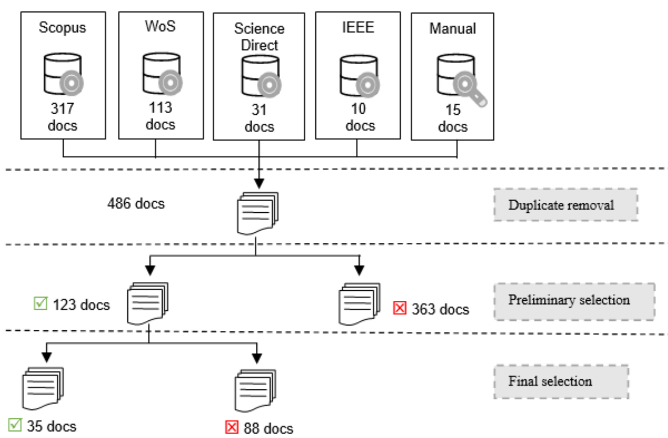

Figure 3: Selection of studies process.

H. Strategy of data summarisation

The form of data extraction described in section D (data extraction form) was used to extract data from 35 documents that had been selected. The data collected as a result of the activity is summarised further in terms of modalities, pre-processing and classification experiment as shown in Figure 4.

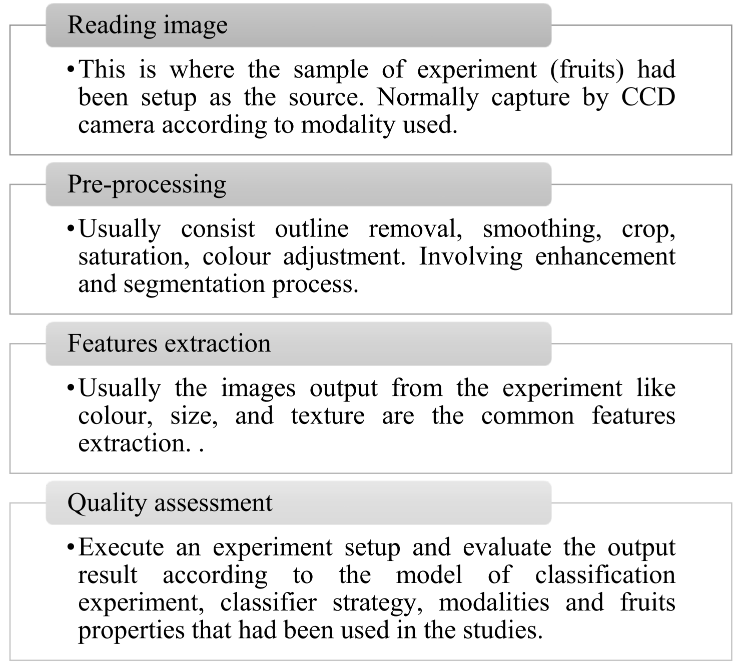

Figure 4: Usual pipeline in fruits quality assessment.

III. RESULT AND DISCUSSION

A. Type of fruits

In the agriculture field, imaging techniques have been widely used especially in fruit quality assessment [12]. Referring to Figure 5, the apple [13]–[15] with 19% is one of the fruits that are very popular that frequently discussed and followed by 11% for strawberry [16]–[19], and pineapple [20], [21]. While banana [11], [22], orange [23]–[25] and peach [26], [27] were at 8%. The least fruit discussed at 3% was figs [28]–[30], limes [31], oil palm [2] and watermelon [32]. Some fruits might be difficult to test in imaging techniques as some fruit has a thick surface and is difficult to analyse by a standard RGB vision system [25]. Another reason is a high end of fruits or not seasonal fruits were difficult to be tested out.

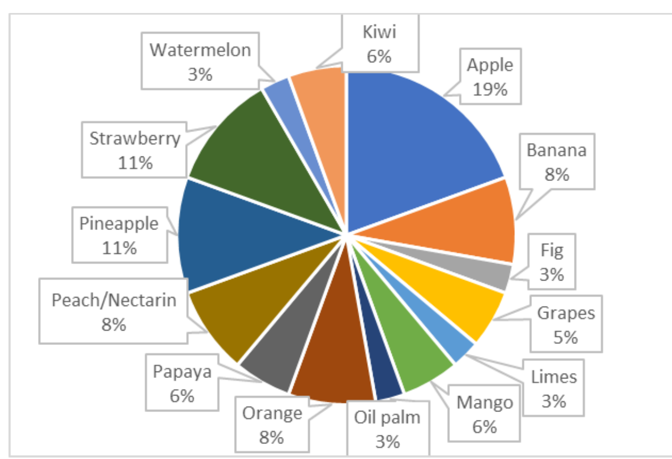

Figure 5: Type of fruits with percentage among 35 papers that has been studied.

Referring to Figure 6, the publication pattern where the percentage of papers published in this research topic was 8%, 11% to 17% between the years 2016 and 2021. While in 2022, the published paper in quality assessment of fruits and image processing picked up the curiosity among the researcher nowadays as the percentage rapidly increased to 31% as shown in Figure 6.

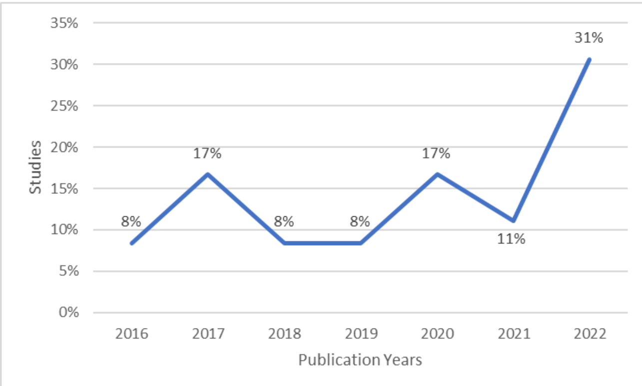

Figure 6: Proportion of image processing of fruit studies over the years.

B. *Imaging modalities*

A variety of modalities are used in quality of fruits assessment such as RGB, Multispectral Imaging (MSI), Hyperspectral Imaging (HSI), Laser-induced backscattering (LBS), Fluorescence Image (FI), X-Ray and Near Infrared (NIR) Spectroscopy had been tested widely. However, some modalities have been improved in terms of parameters and properties such as the light source and wavelength. Recently, J. Prabesh et al., (2022) has been investigated ultraviolet-visible-near-infrared (UV-VIS-NIR) as a perpetuation of a basic configuration NIR by using ultraviolet as a source to monitor and predict the quality of strawberry shelf-life. Some researchers used multiple modalities to get better performance and high accuracy [33]. According to Table 3, MSI and HSI modalities were the most used by the other researcher in fruit quality assessment for most fruits such as apples, bananas, limes, oranges, peach and pineapple. While the others are using LBS, NIR, FI and RGB. The quality of agricultural products can be evaluated using various destructive and non-destructive methods. Most traditional techniques are time-consuming [12] and require a significant amount of manual work [22]. Destructive methods offer a success rate for determining fruit quality, but they have a lot of drawbacks in terms of effectiveness, time, and expense [12]. This is the main reason non-destructive methods have piqued the curiosity of researchers as viable solutions for assessing the quality of fruits [26]. Based on Table 3, most studies only focus on a single modality and technologies where the accuracy and efficiency of the proposed methods are still lower and improvable [1]. To improve those, some studies [13], [15], [34] combine multiple modalities with improving accuracy performance in assessing the quality of fruits. RGB modalities were used in most of the studies as a starting point as this is the basic approach to investigating the quality assessment of the fruits using image processing. However, the hyperspectral approach has always been picked and used by researchers nowadays to assess the quality of fruits.

TABLE III
THE MOST MODALITIES AND METHODS USED FOR DIFFERENT TYPES OF FRUITS

Type of fruits	*Modalities*	*Method*	*References*
Apples	• LBS • MSI • NIR	Non-destructive	[13] [15] [35]
Banana	• HSI • LBS	Destructive Non-destructive	[22] [36]
Fig	• FI • RGB	Non-destructive	[29] [30]
Grapes	• RGB	Non-destructive	[37][38]
Limes	• HSI	Non-destructive	[31]
Mango	• RGB	Non-destructive	[39]
Oil Palm	• LBS	Non-destructive	[2]
Papaya	• LBS	Non-destructive	[40]
Orange	• HSI	Non-destructive	[25]
Peach	• HSI • NIR	Non-destructive	[41] [27]
Pineapple	• MSI	Non-destructive	[42]
Strawberry	• RGB • UV-VIS-NIR	Non-destructive	[18] [16]
Watermelon	• LBS	Non-destructive	[32]
Kiwi	• Microscopic Image	Non-destructive	[43]
Pear	• X-ray	Non-destructive	[44]

In these seven years (2016 to 2022), the use of image modalities is not limited to a certain type of modalities for a specific type of fruit because all image modalities are suitable for all types of fruits. Still, it depends on the researcher's objective and intention. Throughout this investigation, the pattern of frequently used image modalities from 2016 to 2022 shows the validity of these modalities nowadays. Through the full-text read of 35 studies, about ten papers used MSI and HSI to assess the fruit quality while fourteen papers used RGB to combine with other modalities as shown in Figure 7. The another eleven papers used are LBS, NIR and FI as an image modalities in fruit quality assessment.

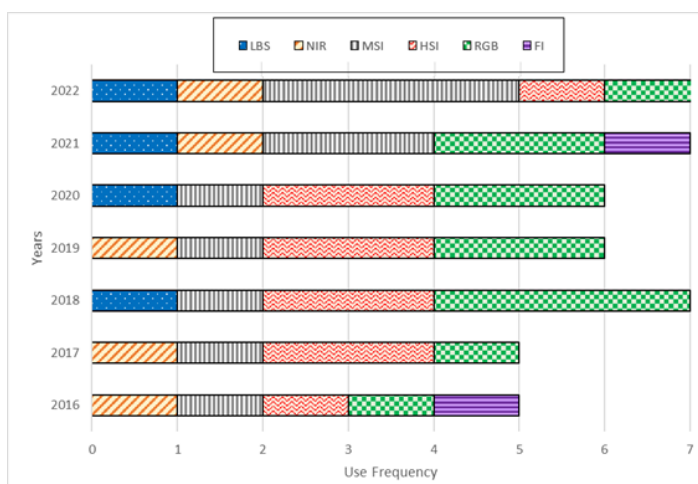

Figure 7: Modalities used from 2016 to 2022.

C. Pre-processing

After the images are obtained using the modalities aforementioned, the fruit image will undergo pre-processing that involves features extraction, filter, enhancement and segmentation.

1. Features extraction

Features extraction in Table 4 shows the preferable features for each fruit mentioned in the table and more than one feature was normally used. We can see most of the researchers will extract the colour and texture of the fruits as favourable features even though the type of fruits was different. This would be the basic approach in quality assessment to predict the external and internal qualities of the fruits such as moisture content, maturity, sugar content, brix value, soluble solids concentration (SSC), titratable acidity (TA), total soluble solid (TTS) or pectin value. This approach shows that most of the research will use multiple features instead of single features. The more combining feature extracted from the model increases the model's ability to be learned and trained to predict the quality of the fruit more accurately. Single features were used because the complexity of determining and extracting the features was obvious or simple. For example, the banana is one of the fruits that we can differentiate the colour either it is already mature or not as the colour becomes darker when it is more mature. While some of the fruits like watermelon, orange and pineapple need to consider multiple features since the colour could lead to false examination as the colours of the fruit remain the same which difficult to classify fruit ripeness stages and other internal qualities assessment. This is why some researchers combine multiple features such as texture that need to be considered as well. This is because the fruits become more softening if the fruits are too mature.

TABLE IV
THE MOST FEATURES EXTRACTION USED FOR DIFFERENT TYPES OF FRUITS.

Studies	***Fruits***	***Features extraction***
[22]	Banana	Texture and colour
[18]	Strawberry	Texture, colour, volume and size
[38]	Grapes	Colour
[45]	Orange	Texture and colour,
[39]	Mango	Colour, volume, and mass
[32]	Watermelon	Texture
[29]	Fig	Colour
[46]	Apple	Colour
[21]	Pineapple	Colour, texture, morphological

2. Filter and enhancement

Image enhancement is the technique of accentuating key aspects of an image while weakening or deleting any extraneous information based on the user's demands. Eliminating noise, uncovering obscured details, and altering levels to highlight parts of an image. As shown in Table 5, about 8 published papers used preferable enhancement methods for each fruit such as shear zones, blurring, colour calibration, light calibration, image resolution and lineaments to improve the quality of the images. However, about 21% of published papers was not used enhancement as their pre-processing method. The enhancement works best on remotely sensed images with Gaussian or near-Gaussian histograms, where all brightness values are confined to a single, narrow range of the histogram and only one mode is visible. This process is very helpful in getting a good and clear image. This is where filtering help contribute to image processing as a filter is needed to remove unwanted features. Referring to Table 5, filtering methods such as Gaussian filter, spectral, Wheel, Cy5.5, Median, UV filter and cross-polarised effect. Two papers used Gaussian Filter to blur images, remove noise detail, and act as a smoothing operator similar to other filters according to the main properties of every filter and experiment. Next, the images will be segmented to remove the region of interest (ROI) from a background [47].

TABLE V
FILTER AND ENHANCEMENT USED BY THE OTHER RESEARCHER IN THEIR STUDY.

Studies	***Filter***	***Enhancement***
[13]	Spectral filter	Colour of the image
[22]	Cross-polarised effect	Hyperspectral diffuse
[48]	Gaussian filter	Light and colour adjustment
[36]	Gaussian filter	Image exposure, no zoom, no flash and binning operation and blurring process
[15]	Wheel filter	Saturation, colour pixel, intensity
[29]	Cy5.5 filter	None
[46]	Median filter	Diffraction image acquisition, rainbow image extraction
[21]	UV filter	None

3. Segmentation

Segmentation is the process of portioning an image into multiple segments known as a set of pixels or image objects [49]. Table 6 shows some of the studies that used threshold as a segmentation method which are effective and helps in processing the partitioning of an image into a foreground and background. This can be explained by separating the background from the picture's region of interest (ROI). This image segmentation technique isolates objects by converting grayscale images into binary images and most of the studies used this method to obtain better results [22], [39], [36]. Automation segmentation such as the IVIS system [29], IVIA software [45], Savitzky-Golay and Bayes theorem [31] will help the segmentation process become easier. Even though the cost can be expensive as a high-end machine is involved. The manual segmentation can be done by removing the background but this will lead to drawbacks such as the accuracy of the results. Other than that, the histogram method is popular among the researcher as popular as the threshold method where the histogram approach method divides the original image into sub-images and applies the thresholding as mentioned above to each image.

TABLE VI
. SEGMENTATION USED BY THE OTHER RESEARCHER IN THEIR STUDY

Studies	***Segmentation***
[22]	ROI, binary image
[48]	ROI and threshold method
[37]	Centroid-based colour segmentation (Euclidean distance)
[45]	Bayes theorem
[31]	Savitzky-Golay
[39]	Binary image and threshold
[25]	Decay region and pseudo-colour image visualisation analysis
[36]	ROI, binary image and thresholding method.
[15]	Image histogram
[29]	Ivis system
[46]	Feature vector representation

D. Classification experiment

Variety of machine learning models that had been used widely such as Support Vector Regression (SVR) or Support Vector Machine (SVM) [50], [51], k-Nearest Neighbor (k-NN) [13], Artificial Neural Network (ANN) [4], [8], [30], [54], [55] , DNN [19], Random Forest (RF) [41], Partial Least-Squares Regression (PLSR) [31] and Convolutional Neural Network (CNN) [14], [19], [28], [56] in fruits quality assessment as shown in Table 7. All of these methods depend on the characteristics and specifications of the researcher according to their studies. Neural network approaches are probably the most well-known among the researcher either for classification and prediction purposes.

TABLE VII
CLASSIFICATION EXPERIMENT WITH DATA SAMPLE AVAILABILITY

Studies	***Fruit***	***Data Sample***	***Classification Method***
[41]	Peach	Private database	Neural network (SAE-RF)
[31]	Limes	Private database	PLSR, PCA
[42]	Pineapple	Private database	ANN k-NN, SVM, PLSR
[28]	Fig	Private database	YOLO v4 with faster R-CNN
[46]	Apple	Private database	SVM, k-NN
[24]	Orange	Hopfield	ANN
[11]	Banana	Private database	k-NN
[57]	Oil palm	FAOSTAT	SVM, ANN
[16]	Strawberry	Private database	PLSR

The most significant advantage of neural network approaches in general is that they can handle a problem with a large number of parameters and categorise items accurately even when the distribution of objects in the parameter space is extremely complex. CNN, PLSR and k-NN have been used widely as learning algorithms for supervised learning tasks and data sets. By referring to Table 7, we can see that most of the researchers [21], [31], [46] used more than one ML or deep learning to classify and regress the dataset which helps a better result in the end. Through the full-text read of nine studies, about two papers stated their database (Hopfield and FAOSTAT) while others used private databases or their own dataset.

Throughout this investigation, the pattern of frequently used classifier from 2016 to 2022 shows an expansion of neural network methods as compared to the others. It can be clearly seen and proven in Figure 8 where the CNN and PLSR models are frequently used for quality assessments based on the current trends. Through the full-text read of 35 studies, about ten papers used CNN to assess the fruit quality while nine papers used PLSR instead. Another 16 papers used k-NN, ANN, SVM, SVR and RF classification methods.

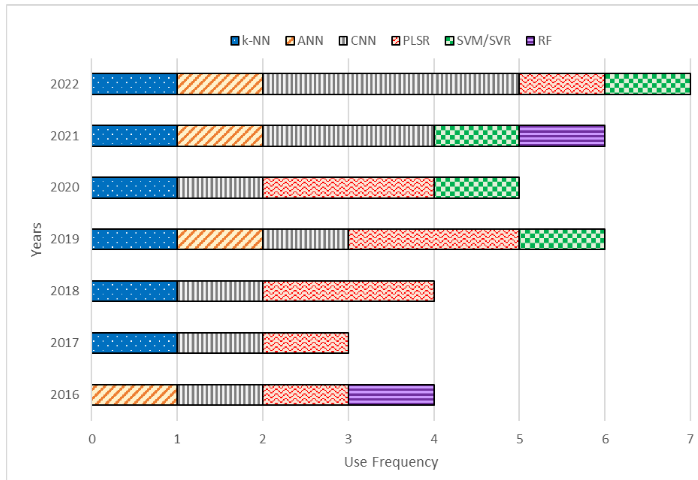

Figure 8: Classifier method used from 2016 to 2022.

Referring to Table 8, five published papers with prediction and six for classification that expected result of a test derived to evaluate the stated parameters. Performance evaluations for prediction such as R^2 coefficient of determination, R_P^2 (coefficient of prediction), and RMSEP (root mean square error of prediction) was used to assess the external and internal qualities such as maturity, moisture content, TSS, TA, SSC colour, and texture [22]. According to C. S. Nugroho et al., [18], the classification performance evaluations can be concluded as accuracy in percentage. This makes the result obvious for the reader to comprehend the use of modalities, methods and techniques. In Table 8, about six over eleven researchers used prediction in quality assessment while another four used classifications. This classifier strategy depends on the output the researcher wants. For example, prediction is normally used to predict the value of internal or external quality of the fruits while classification is used to classify the quality of the fruits based on ripening stages. Throughout this investigation, we can see that the classification strategy had become popular among the researcher due to the industry demand [51].

TABLE VIII
FRUITS CLASSIFIER STRATEGY WITH THEIR PARAMETER PERFORMANCE VALUE

Studies	***Fruits***	***Classifier Method***	***Classifier Strategy***	***Parameters***	***Performance Value***
[22]	Banana	PLSR	Prediction	Moisture content Texture Colour (b*, a* and L*)	R_P^2= 0.97, RMSEP = 0.05 kg water/kg DM) R_P^2= 0.66, RMSEP = 11.8 N) b* value (R_P^2= 0.83, RMSEP = 1.95) a* value (R_P^2= 0.53, RMSEP = 1.32) L* value (R_P^2= 0.61, RMSEP = 5.92)
[16]	Strawberry	PLSR	Prediction	Appearance	R^2=0.97
[19]	Strawberry	CNN	Classification	Wavelength	Accuracy = 98.6%
[41]	Peach	SAE-RF	Prediction	SSC	(R^2= 0.9184, RMSE = 0.6693)
[38]	Grapes	RF	Classification	Colour (L*, a*, b*)	Accuracy=92%-100%
[45]	Orange	PLS-DA	Classification	PLS-DA model	Accuracy=96%
[31]	Limes	PLSR	Prediction	TSS TA Maturity index	R_P^2=0.838, RMSEP=0.237% R_P^2=0.694, RMSEP=0.288% R_P^2=0.775, RMSEP=0.049
[15]	Apple	Backward-PLS	Prediction	Sugar content, r Brix value	r =0.8861 RMSEC=0.8738°
[46] [14]	Apple	SVM CNN	Classification Classification	Colour Colour	Accuracy=93-100% Accuracy=96.5%
[30]	Figs	ANN	Classification	Pectin Value Colour	Accuracy= 77.78% Accuracy= 91.67%

IV. CONCLUSION

The results of the systematic review given in this paper allow for the description of three important features of quality evaluation using an imaging technique that was published between 2016 and 2022 image processing which is a type of fruits, modalities, pre-processing that include feature extraction, enhancement, segmentation, and classification experiments. Most studies use HSI and MSI modalities with a promising result of powerful detection that allows us to see beyond the human limitation and capture valuable information across the photonic spectrum. Still, it is costly compared to other modalities such as LBS. Apples have become the most frequent fruits that have been discussed while the least fruits are oil palm and fig fruits due to each fruit having different properties such the colour, skin type, and texture. Besides, feature extractions normally used were colour and textures as the common approach in fruity quality assessment. About 50% of the study used neural network machine learning as the common method to assess the quality of fruits.

Furthermore, methodological concerns have been identified as the main challenge in investigating the quality of fruits. Regardless, we find in image processing studies the importance of overlooking information concerning modalities and ML. Not all the methods had been discussed specifically as the data may lead to undesirable consequences in the area such as redundant data, unfair comparisons, and producing inaccurate results or conclusions. We recognise that absolute agreement on the experimental methodologies for quality assessment utilising image processing is impossible because scientific investigations are not strict but rather opportunistic. By conducting this SLR, in relation to our research in quality assessment of figs fruits using imaging techniques give a tremendous help as we can improve and choose which strategies are suitable in terms of modalities, classifier strategy, pre-processing and which fruits we can benefit more in this community. However, properly clarifying methodological factors is also beneficial to this study community. To that aim, we used the findings in this systematic review paper to describe critical methodological considerations that in our opinion it will be of significant value to future research.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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