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REVIEW ARTICLE

A systematic review and comparative meta-analysis of non-destructive fruit maturity detection techniques

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Abstract

The global fruit industry is growing rapidly due to increased awareness of the health benefits associated with fruit consumption. Fruit maturity detection plays a crucial role in fruit logistics and maintenance, enabling farmers and fruit industries to grade fruits and develop sustainable policies for enhanced profitability and service quality. Non-destructive fruit maturity detection methods have gained significant attention, especially with advancements in machine vision and spectroscopic techniques. This systematic review provides a concise overview of the techniques and algorithms used in fruit quality grading by farmers and industries. The study reviewed 63 full-text articles published between 2012 and 2023 along with their bibliometric analysis. Qualitative analysis revealed that researchers from various disciplines contributed to this field, with techniques falling into 3 categories: machine vision (mathematical modelling or deep learning), spectroscopy and other miscellaneous approaches. There was a high level of diversity among these categories, as indicated by an I-square value of 88.37% in the heterogeneity analysis. Meta-analysis, using odds ratios as the effect measure, established the relationship between techniques and their accuracy. Machine vision showed a positive correlation with accuracy across different categories. Additionally, Egger's and Begg's tests were used to assess publication bias and no strong evidence of its occurrence was found. This study offers valuable insights into the advantages and limitations of various fruit maturity detection techniques. For employing statistical and meta-analytical methods, key factors such as accuracy and sample size have been considered. These findings will aid in the development of effective strategies for fruit quality assessment.

Keywords

Image processing; machine vision; spectroscopy; maturity detection; fruit maturity; mathematical modelling

Introduction

In the era of globalisation, consumer's preference for fresh and high-quality produce has experienced a significant surge. Their demand for flavourful produce with abundant nutritional value has increased exponentially (1-3). To meet these expectations, the ability to harvest fruit at the precise moment of peak maturity plays a crucial role. However, determining this optimal harvesting time poses a major challenge in the agricultural sector. The concept of fruit maturity encompasses a range of factors, including sugar content, acidity levels, firmness, color development and other internal attributes (4-7). Conventionally, fruit quality assessment relied on visual inspection and quantitative approaches such as hardness analysis, total soluble solid content analysis, ethylene content measurement and gas chromatography (8, 9). These methods consumed a significant amount of time and manual labour, often yielding inconsistent results (10-13). Furthermore, many of these techniques are invasive in nature, which can lead to the loss of valuable produce, impacting profitability (14-17).

Fortunately, with advancements in technology, multiple non-destructive techniques have emerged as promising alternative to conventional approaches. These techniques utilize cutting-edge technologies and advanced algorithms to estimate critical quality parameters. Popular approaches for estimating fruit maturity include machine vision, spectroscopy-based methods, or a combination of both. Other techniques, such as acoustics and computed tomography, also exist for estimating fruit maturity (18). In machine-based sensing, grading and sorting fruits into different maturity categories are typically based on the fruit's size, volume and shape (19). For instance, it was estimated the maturity of oil palm fruits using a machine vision approach and achieving an accuracy of 98.3% (20); Reports are on the usage of an RGB color-based technique to estimate fruit maturity with an accuracy of 95% (21). Reports are also on the estimation of fruit maturity using digital images through Convolutional Neural Network (CNN or ConvNet) and achieving an accuracy of 92% (22). One of the major advantages of using machine vision techniques is the low instrumentation cost and quick results (23). However, challenges such as background light interference and the dependence on digital image processing information poses a significant obstacles for on-field implementation of the technique (18).

Another popular approach for fruit maturity classification includes spectroscopy-based techniques such as Visible Near-Infrared Spectroscopy, Hyperspectral Imaging and more. These techniques are utilized to evaluate multiple maturity indices such as soluble solid content, firmness, potential of hydrogen (pH) and other chemical attributes that change as the fruit undergoes ripening (24). For example, reports are on the Savitzky-Golay smoothing and first derivative (1D) (SGD1) spectral preprocessing technique to determine quality of Japanese table grapes with an accuracy of 93.1% (25). Observations are on the usage of dry matter content as a maturity index for estimating the ripeness of durian through Near- Infrared Region (NIR) spectroscopy with an accuracy of 94.4% (26). Reports are also on the utilisation of dry matter content, soluble solids concentration and the index of absorbance difference to estimate quality and maturity of peach fruit using Near-Infrared Spectroscopy (27). The spectroscopic technique inspects internal attributes while estimating the maturity of fruits, making it more comprehensive than machine vision-based techniques that uses digital images. However, the high computational cost and the ability to detect only a small portion of the entire fruit poses some significant challenges in the implementation of these techniques (28, 29). Some other popular techniques include laser Doppler vibrometry or acoustics-based approach. For example, utilised Laser Doppler Vibrometry (LDV) derived fruit signatures for the maturity classification of fruits (30), while another study employed laser-light backscattering imaging with an average accuracy of 85% to determine the maturity stage of oil palm fruits (23).

This systematic review and meta-analysis aims to analyze various non-destructive techniques used in the maturity classification of fruits. It will enhance the current knowledge base and provide valuable insights to researchers and practitioners regarding the capabilities and constraints of these techniques. Additionally, further research and development of these techniques could also aid in estimating the mass (31-34) and volume of fruits (35-38), crucial factors for commercial quality evaluation.

This study presents a systematic review and meta-analysis focusing on the application of non-destructive techniques for maturity classification. The key objectives of the study are as follows:

(i) To examine various non-destructive techniques for maturity classification and understand their strengths and limitations.

(ii) To identify research gaps and areas for improvement, thus strengthening the research on the topic.

(iii) To determine the effect size by analyzing odds ratio and confidence intervals.

(iv) To assess the predictive performance of studies for the maturity classification of fruits.

Research Methodology

Eligibility criteria

To ensure the selection of high-quality research papers for systematic review and meta-analysis that align perfectly with the research objective and questions, the following criteria have been considered:

Relevancy

The title, keywords and abstract of the article must match the research questions and objective.

Duplicates

To maintain information uniqueness, identical papers have been removed through manual checks and software support.

Publication type and date

Papers such as letters, books, commentaries etc. were excluded. The timeframe considered for the paper is from 2012 to 2023.

Language

Only papers published in English have been preferred for the review analysis.

Information sources

Papers were gathered from several popular databases, including AGRICOLA, Scopus, Taylor & Francis, Web of Science, Google Scholar, Semantic Scholar and PubMed.

Search strategy

For the systematic review and meta-analysis of fruit maturity detection studies, research papers were selected using the PRISMA methodology as illustrated in Fig. 1. Inclusion and exclusion criteria were applied to identify the most suitable paper. Various queries, aligned with fruit maturity detection, were developed for different databases using specific keywords:

Digital image analysis, Image processing, Computer vision, Machine learning, Non-destructive, Fruit volume estimation, Fruit measurement, Fruit sizing, Fruit grading, Fruit quality assessment, 3D reconstruction, Image segmentation, Feature extraction, Image-based modelling, Non-invasive measurement, Remote sensing, Hyperspectral imaging, NIR imaging, Fruit and Crop.

Inclusion and exclusion criteria

Initially, papers focusing on fruit maturity detection published in English between 2012 to 2023 were retrieved from different databases. A total of 856 papers were extracted, out of which 185 were excluded as they did not

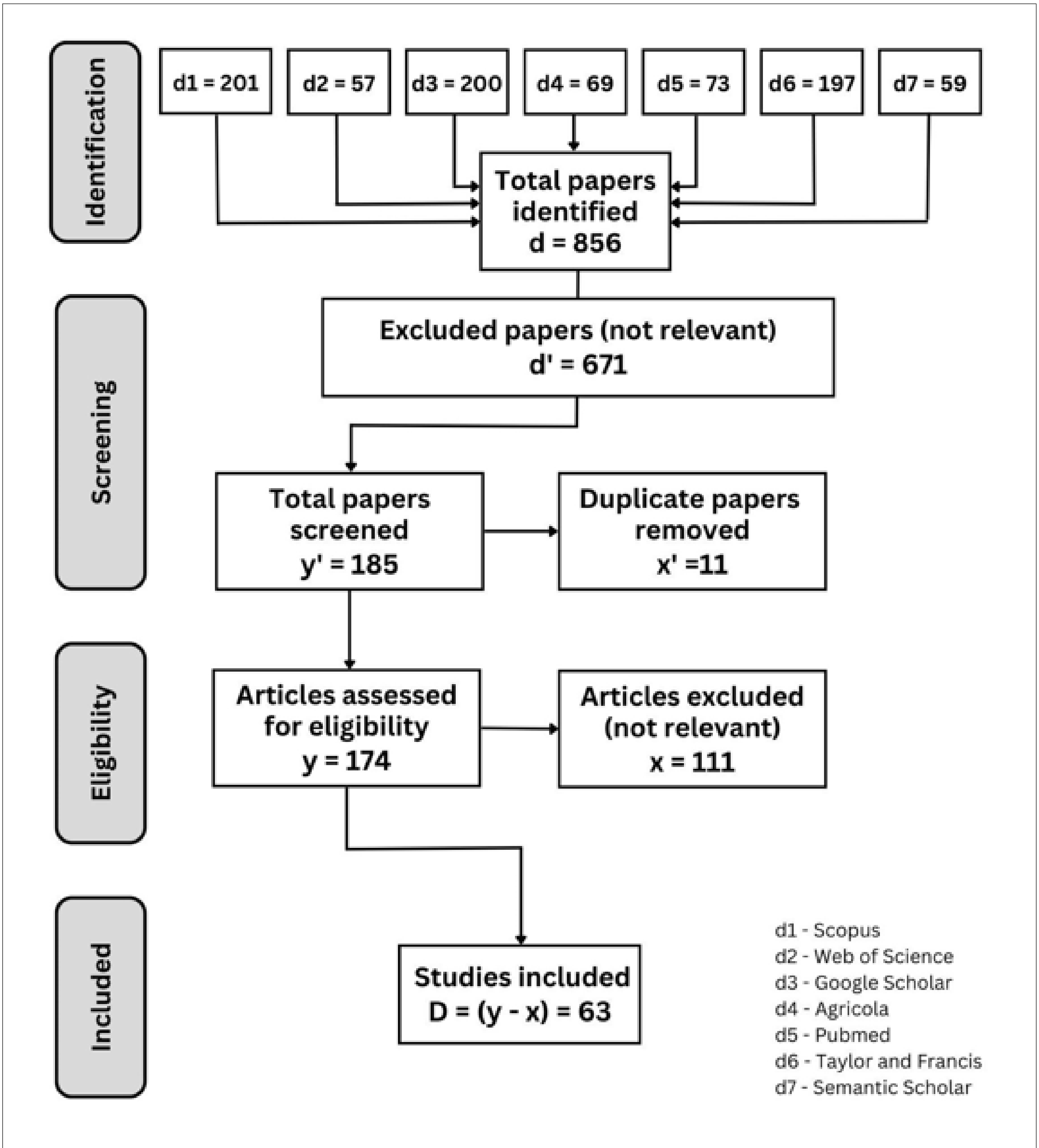


Fig. 1. PRISMA flowchart to find best-fit papers for the systematic review and meta-analysis.

align with the research objectives. To eliminate duplicates, 11 more papers were removed. Finally, out of the remaining 174 papers, 111 were excluded due to their similar methodologies and information. In the end, a set of 63 high-quality papers were selected for the review analysis.

Quality assessment

To ensure the maintenance of quality, the following points were considered and applied manually:

- Area of interest and methodology: papers had to be directly related to fruit maturity detection.
- Dataset: Each paper must present distinct and tested information.
- Risk of Bias and performance: The literature review was examined by multiple researchers to reduce the risk of bias, focusing on parameters such as accuracy and sample size.

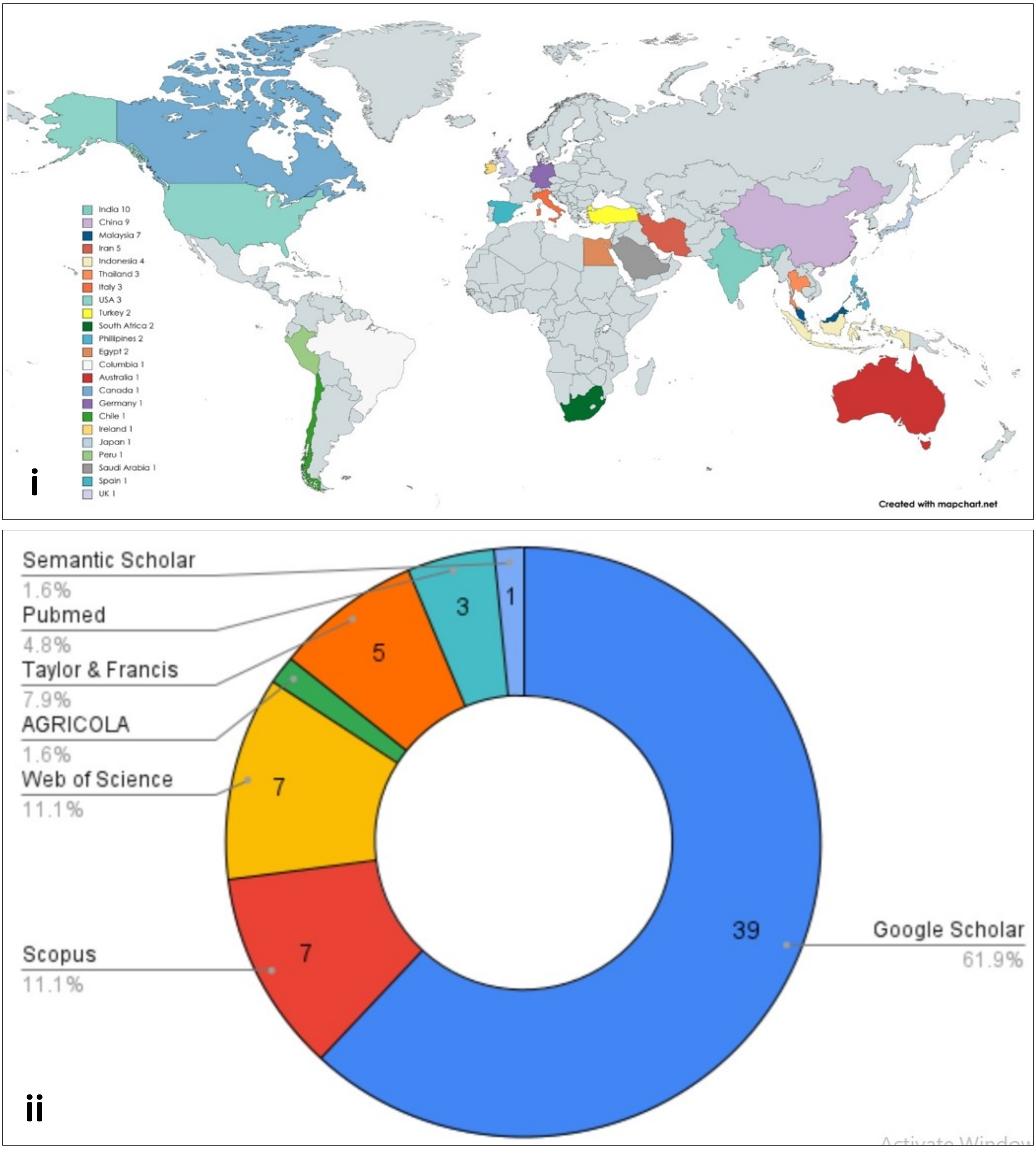
Bibliometric analysis

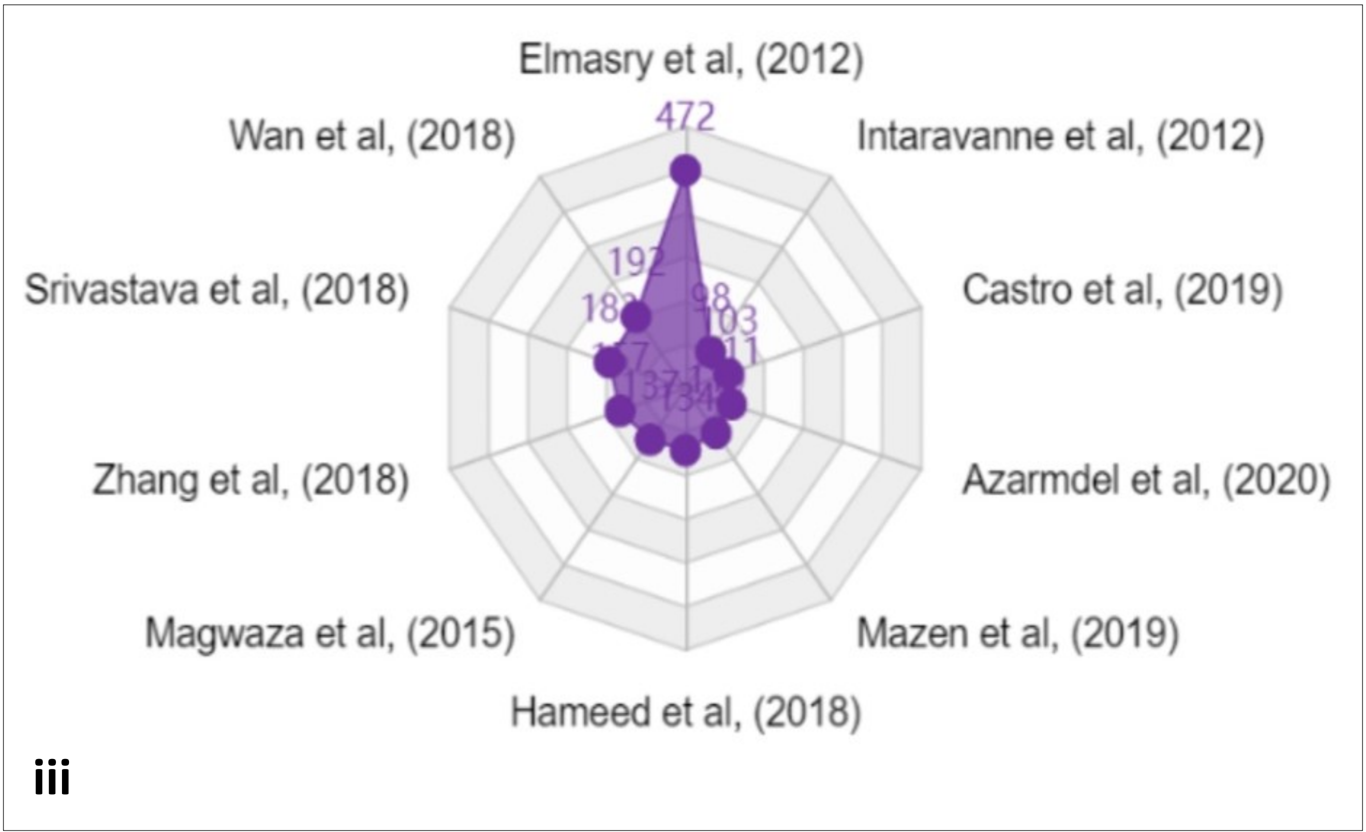
Geo chart for publications by country

Asian countries led in research publications on this topic compared to any other continent between 2012 and 2023 (Fig. 2 (i)).

Pie chart for publications by database

The majority of papers based on this subject were obtained through Google Scholar 61.9%, followed by Scopus and Web of Science both at 11.1%, respectively (Fig. 2 (ii)).

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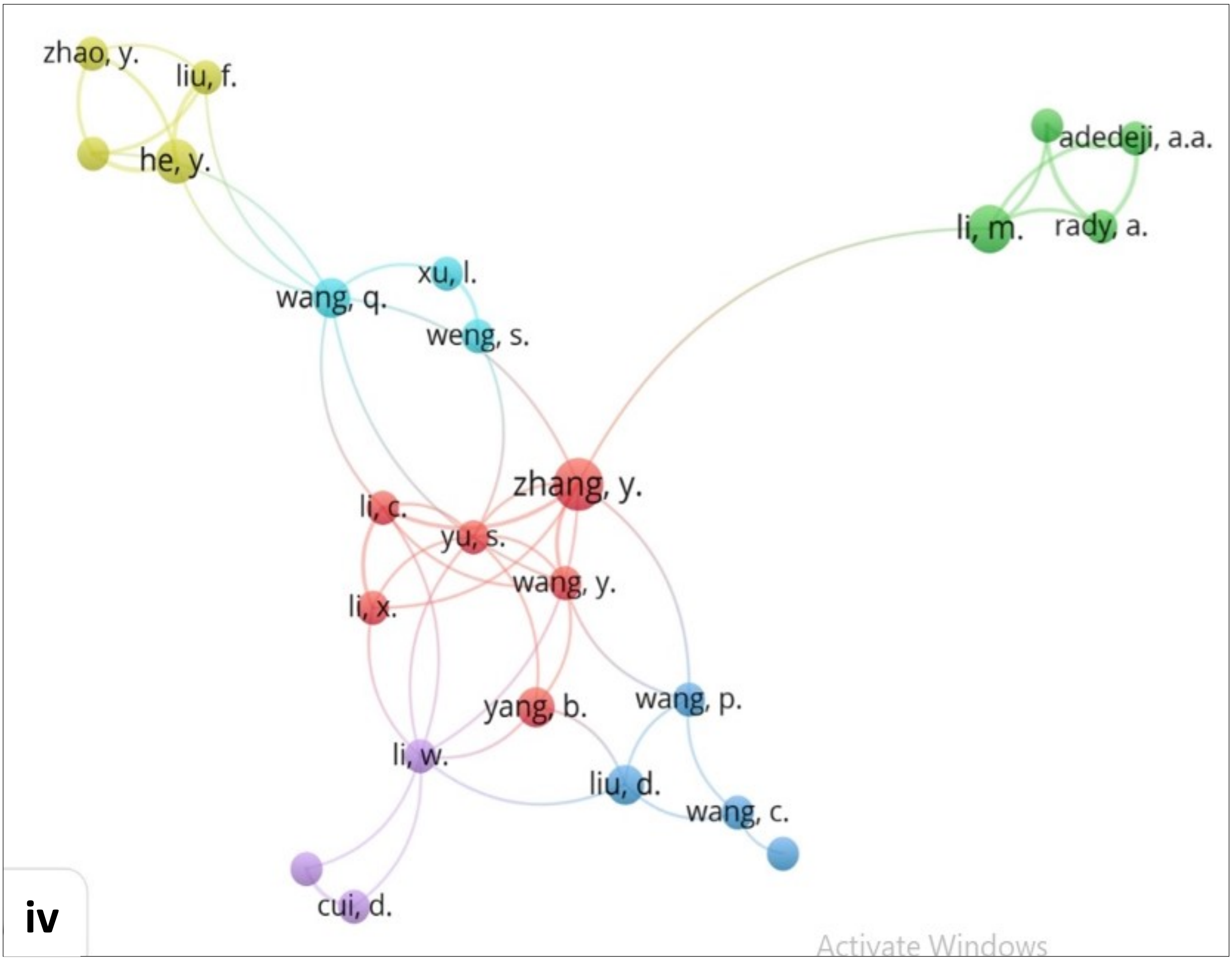
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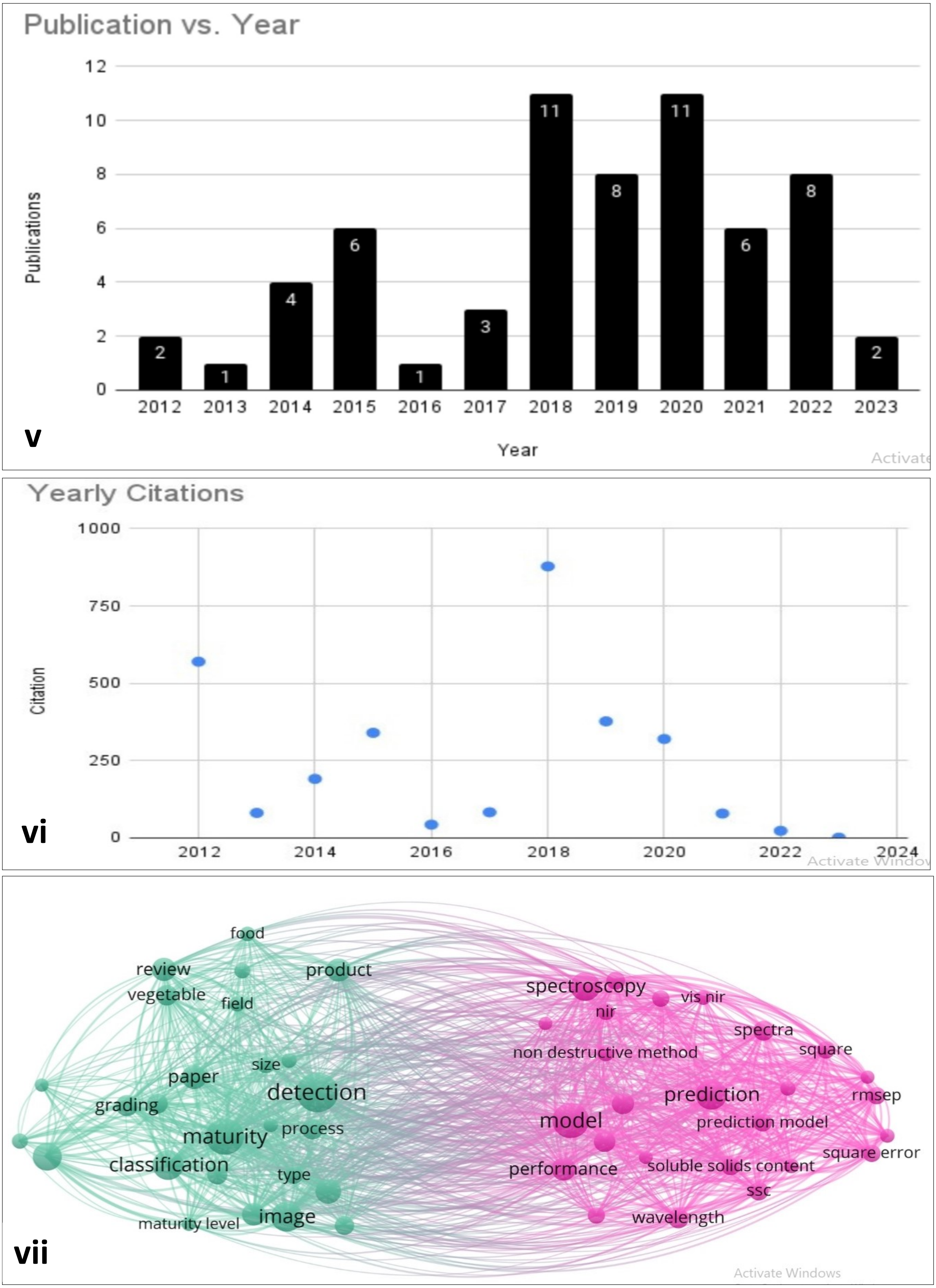

Fig. 2. (**i**) Total number of publications by different countries; (**ii**) Database contributions expressed as percentage; (**iii**) Papers with most citations; (**iv**) Contribution to various articles as a co-author; (**v**) The total number of papers published in each year; (**vi**) Overall number of citations over the years; (**vii**) Different papers co-occurring with different keywords.

Bar chart for year vs publications

In Fig. 2 (v), the cumulative publication count for fruit maturity estimation using Machine Vision, Spectroscopy, and other miscellaneous approaches is shown. The figure illustrates that researchers began exploring this field in 2016, with a peak in publications observed in 2018 and 2020.

Bubble plot for seeking trend of citation

From Fig. 2 (vi), it is evident that most citations in the research domain were made in 2018, indicating significant interest in the topic.

Radar chart for most cited papers

Fig. 2 (iii) highlights the most cited papers in a radar chart. It is evident that (1) had the most citations, standing at 472, followed by (39) and (18) with 192 and 183 citations respectively. These are then followed by the papers (3, 6, 28, 40, 41 ,42, 8).

Network analysis by coauthors

As shown in Fig. 2 (iv), the co-authorship was analysed to represent coauthors in the network chart. The software employed for the analysis was VOS viewer version 1.6.18. Co-authored articles signify relatedness and 24 authors met the threshold of 3 documents.

Network analysis by keywords

In Fig. 2 (vii), various keywords are shown on a map. The analysis was conducted using VOS viewer version 1.6.18, with a minimum threshold set at 25 keywords. The network has been divided into two clusters. Articles focusing on 'Image processing' dominated the landscape, while 'Review papers' had the smallest presence, indicating fewer studies conducted on this topic.

Materials and Methods

The presented systematic review and meta-analysis is based on 63 studies collected from multiple databases. Visualizing charts were created using different python libraries like matplotlib and seaborn. VOSviewer version 1.6.18 was employed for network charts. Statistical analysis using proportions was also performed to assess heterogeneity and publication bias within the collected literature. The study encompassed a total of 63 research articles, including 10 review papers. Out of these, 53 articles were meticulously scrutinized to extract techniques for assessing maturity. Following a rigorous evaluation, considering factors such as sample size, accuracy and technique type, a subset of 21 papers was chosen for the statistical evaluation of the overall population.

Useful terminology

Sample Size

It is the number of fruits used in a particular technique to detect maturity. It represents the size of the dataset or the number of observations on which the technique is applied.

Accuracy

Accuracy measures how well each technique is able to correctly identify the maturity of the fruits. It is typically expressed as a percentage and represents the proportion of correct identifications out of all the identifications made by the technique.

Odds ratio (OR)

The odds ratio is a measure of the association between exposure and an outcome. It compares the odds of an outcome occurring given a particular exposure to the odds of an outcome occurring in the absence of that exposure.

Confidence Interval (CI)

A confidence interval is a range of values that is likely to contain the true value of a parameter with a certain level of confidence.

Fixed Weights

Fixed weights are a set of predetermined weights assigned to each category of techniques. These weights can represent the importance or preference given to each technique in the analysis. Fixed weights remain constant throughout the analysis.

Random Weights

Random weights are weights that can vary or be assigned through a random process. They can be used to assess the sensitivity of the analysis to different weightings of the techniques.

Q-Statistic

The Q statistic measures the total amount of variation or heterogeneity among a set of studies or data points. It is calculated by summing the squared differences between each study's effect size and the overall effect size, weighted by the inverse of the variance of each study.

Degree of Freedom (DF)

Degrees of freedom represent the number of values in the final calculation of the Q-statistic that can vary without affecting its value.

I^2 (I-squared) Statistic

I^2 quantifies the proportion of total variation in effect sizes across studies that is due to true heterogeneity rather than chance.

Intercept

The intercept indicates the degree of funnel plot asymmetry. If there is no publication bias, the intercept should be close to zero. A significant positive intercept suggests that there may be publication bias, with smaller, less precise studies showing more extreme effect sizes.

Kendall's Tau

It is a measure of the correlation between the effect size of each study and its variance.

Significance Level (α)

The significance level, denoted as α, is a predefined threshold used in hypothesis testing to determine the level of significance or the acceptable probability of making a Type I error.

Calculation of odds ratio and confidence intervals

Based on the data gathered and reported in Table 1, the likelihood of papers using a specific approach with over 90% accuracy were calculated using odds ratio. For obtaining the ratios, *a*, *b*, *c* and *d* representing count of papers with over 90% accuracy following an approach, with less than 90% accuracy following that approach, with over 90% accuracy not following that approach and with less than 90% accuracy not following that approach respectively were determined. The odds ratio of a paper with over 90% accuracy following a specific approach was calculated by $\frac{ad}{bc}$

For the confidence interval of 95% the following expressions were used,

$$\text{Upper 95\% CI} = e^{\ln(OR)+1.96\sqrt{\frac{1}{a}+\frac{1}{b}+\frac{1}{c}+\frac{1}{d}}}$$

$$\text{Lower 95\% CI} = e^{\ln(OR)-1.96\sqrt{\frac{1}{a}+\frac{1}{b}+\frac{1}{c}+\frac{1}{d}}}$$

Heterogeneity analysis

Cochran's Q test was employed to assess heterogeneity. Two hypotheses were formulated: (i) All the 3 approaches are equally effective for fruit maturity estimation; (ii) All the 3 approaches are not equally effective in fruit maturity estimation. Hypothesis testing was carried out using MedCalc statistical software version 22.007 and I^2 was calculated to quantify the degree of inconsistency. The significance level was set at 0.05. The analysis utilized mean sample size and mean accuracy from studies following specific approach as the raw input, with other statistical measures calculated by the software for result interpretation.

Egger's and Begg's test

Publication bias was evaluated through Egger's and Begg's test. Under this, the following hypotheses were formulated: (i) There exists no strong evidence of publication bias in the selection of studies; (ii) There exists publication bias in the selection of studies. For testing these hypotheses, MedCalc Statistical Software version 22.007 was utilized and a funnel plot (Fig. 3) was charted for visual inspection of the asymmetry. The significance level was taken as 0.05 for the analysis. The input for further analysis included sample size and mean accuracy of each individual study, with other statistical measures computed by the software for interpretation.

Literature review

Among the selected 63 studies, a significant portion of the literature focused on machine vision and advanced spectroscopy technologies as non-destructive fruit maturity detection techniques. Additionally, promising results were achieved with techniques based on laser technology, leading to their classification under the third category of other miscellaneous approaches. It is noteworthy that these 3 approaches are used in almost all of the investigated studies. In brief, the approaches can be summarized as follows:

Machine vision approaches

Machine vision techniques, incorporating mathematical modelling and deep learning, can emulate the human ability to classify fruits into ripe, unripe, or partially ripe categories. Inspired by human vision, these techniques surpass human limitation, enabling faster, more precise and accurate evaluation of fruit samples.

Vision sensing is widely employed through colour-based image processing algorithms. For instance, reports are on the utilization of colour distribution analysis and back projection to evaluate the maturity and quality of harvested dates (21). A commercial inspection system equipped with colour cameras captured images of dates. Image analysis techniques were then applied to segregate the data area from the background based on the images. The proposed algorithm generated a 2D histogram using the red and green values of the pixels, analysing the colour of the dates. Input colour values were mapped to predefined colour indices using a back-projection matrix generated from normalized histograms. This analysis resulted in a colour grading matrix, determining the maturity and quality of the dates. The Otsu method was used to separate the oil palm fruit region from the background in the image, resulting in an iterative threshold to enhance the

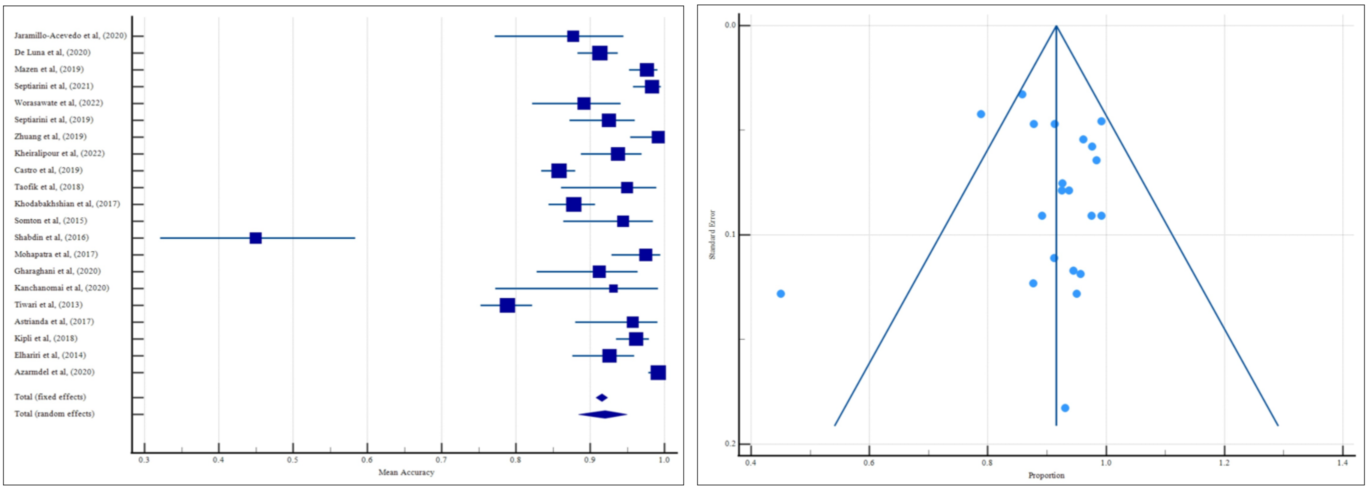

Fig. 3. Forest plot (Left) and funnel plot (Right) for visualizing data.

technique's performance (43). However, reports are on the collection of images to train a deep learning model using Artificial Neural Network (44).

Numerous advanced artificial intelligence algorithms have been harnessed to enhace the efficiency of the system. Furthermore, recent advancements in machine vision, coupled with mathematical formulations, have become a central focus for researchers addressing multifaceted challenges in agriculture. Recent reviews by the authors (60-62) understood the significance of mathematical models and other techniques in crop yield forecasts. Additionally, this modelling approach has been recently applied for yield estimation specific to baby corn (63).

Spectroscopy based approaches

The ripeness level and the correlated volume of a fruit are intricately linked to its internal characteristics including colour, acidity, moisture content (MC), dry matter content (DMC), total soluble solids (TSS) and firmness (F). Spectroscopy-based approach are adept at estimating the correct ripeness level and its corresponding volume. These techniques can extract internal fruit quality parameters using UV–Vis–NIR and Mid-infrared radiation (MIR) spectrum, based on the measurement of the total diffused reflected signal at different wavelength bands.

A spectrophotometer with a wavelength range of 285 to 1200 nm was used (45). During training sets, the fruit samples (Barhi date) were placed on the instrument lens in setup mode to measure the spectrum parameters. Subsequently, the physical characteristics of fruits (Total Soluble Solid, Moisture Content, and colour) were measured in alignment with the spectrum data. Then Data Viewer Software was used to sort and examine the data (45). At the range of 285-1200 nm, the first and second derivatives were correlated using Model Builder. The derivatives were used to predict the model of the spectrum with reference values.

Further, these first and second derivatives were correlated at (285-1200 nm) using Model Builder which was used to forecast the model of the spectrum with those reference values. Observations are also on the strong correlations in Barhi quality parameters, with a high coefficient of determination (R^2) values of 0.97 for TSS, 0.94 for MC and 0.64 for colour (45).

Other miscellaneous approaches

This category encompasses techniques beyond machine vision and spectroscopy, incorporating hybrid techniques like hyperspectral imaging or actively developing methodologies based on lasers. While not as widely recognized as other approaches, these techniques hold promising potential.

Hyperspectral imaging

The technique of hyperspectral imaging is gaining traction by integrating conventional image processing with spectroscopy, enabling the extraction of both spectral and spatial information from different fruit samples. For example, reports are also on a study involving 450 uniformly sized pear fruits without physical defects at 90, 100 and 110 days after Full Bloom (DAFB) (4). They categorized the ripeness of the fruits into 3 distinct levels based on a subjective assessment of the skin texture. To analyze the images within the wavelength range of 425 to 1000 nm, a hyperspectral imaging system with a spectral resolution of approximately 2.8 nm and a range from 325 to 1100 nm was employed. Subsequently, each fruit sample was examined for firmness and SSC (soluble solid content). Initial firmness measurement were conducted using a fruit sclerometer equipped with a 3.5 mm Magness-Taylor (MT) probe, ensuring accuracy up to 0.1 N. However, hyperspectral imaging poses several challenges, including spatial resolution issues, variations in spatial radiation and sample surface nature, pixel size limitations, and irregularities on the measured surface. Additionally, compared to other non-contact sensing techniques, hyperspectral imaging demands higher hardware capabilities and computational resources.

Scanning laser doppler vibrometry (SLDV)

SLDV, a powerful characterization technique based on visual interferometry principles effectively tackles vibration-related challenges. It precisely measures surface velocities of point grids at frequencies up to 30 MHz, enabling vibration measurement and potential assessment of mechanical properties in highly dampened materials (46).

For example, there are reports on the utilization of SLDV in 2 experiments with Chilean and Spanish fruits (30). In the first experiment with Chilean fruit, they employed a LabVIEW algorithm to obtain vibration time signals at a sampling frequency of 20 kHz. Resonant frequencies (RF) were calculated using an exponential window in MATLAB, Fast Fourier Transform (FFT), and a high-pass filter. The first peak in the frequency spectra represented the resonant frequency (RF) of the initial spheroidal mode observed in all fruits. Fruit stiffness (S) was determined using a formula applicable to spherical objects. In the second experiment with Spanish fruit, a sampling frequency of 40 kHz was used. Three signals per laser were multiplied together, and the RF of the first peak was recorded. Damping properties were assessed by processing the time signal, including bandpass filtering, absolute value calculation, and application of an exponential function as a vibration signal envelope. An attenuation coefficient describing vibration dampening extent was derived. Various techniques, such as applying an exponential window, FFT and spectral smoothing, were employed to obtain resonant frequency values for further analysis. Parameters such as the first spheroidal mode resonance frequency at its highest amplitude, damping factor and standard squared error of damping were recorded for each case. Damping values with high squared errors were disregarded during data analysis. Subsequently, appropriate statistical tests were conducted using Genstat software to assess the goodness of fit between measured and predicted values for both experiments.

Laser-light backscattering imaging

Laser-light backscattering is a technique employed to assess the textural and mechanical properties of fruits.

This method has been successfully used to classify the ripeness of various fruits, including apricot, banana and macaw oil palm (47), as demonstrated (23). In their study, 90 fresh fruit bunches (FFB) of the DXP GH 500 Golden Hope variety were examined, with 30 FFB representing each maturity level (unripe, ripe and overripe). After capturing images of the FFB samples, the oil content at each maturity level was determined using the Soxhlet technique. An optical imaging system was employed for data collection, consisting of a laser diode, 2 fluorescent lamps, a charge-coupled device (CCD) camera and a computer with imaging software. This system captured both RGB and backscattering images. MATLAB was utilized for segmenting the RGB images and extracting required features from the backscattering region based on different intensities of pixels. The analysis parameters included axis length (major and minor), perimeter and mean intensity. To analyze the quality variations of FFB in oil palm based on their maturity levels, principal component analysis (PCA) and partial least squares (PLS) techniques were applied. Linear and quadratic discriminant analyses were used to evaluate the classification performance by incorporating both RGB and backscattering data. The FFB maturity level exhibited average accuracies exceeding 85% in oil palm assessment.

Results from analysis

Bibliometric analysis

In the realm of discussed research, Asian countries emerged as the leading contributors, generating a substantial number of publications. Google Scholar served as the primary source for collecting research articles, closely followed by Scopus and Web of Science. Notably, research interest in fruit maturity detection peaked in 2018 and 2020, marked by a significant number of citations in 2018. Particularly, paper (1) garnered exceptional attention, amassing 472 citations over the considered decade, underscoring its profound impact in the field. Additionally, an analysis of keywords within the network revealed a dominance of articles focused on 'image processing.' Moreover, coauthor network analysis identified 24 authors who surpassed the threshold of 3 documents, emphasizing the collaborative nature of this vibrant research area since 2016. These intricate findings collectively signify the active and expansive nature of this research theme.

Statistical analysis

The odds ratio was employed to gauge the likelihood of papers, employing specific approaches, achieving an accuracy exceeding 90% compared to other methodologies. In the context of machine vision through mathematical modelling, an odds ratio of 2.75 was calculated, signifying that papers utilizing this method were 2.75 times more likely to achieve over 90% accuracy compared to alternative techniques. The corresponding 90% confidence interval of (0.53, 14.33) provides insights into the probable range of odds ratios in 90% of instances. Conversely, for spectroscopy, the odds ratio stood at 0.31, indicating that papers employing this technique were 0.31 times less likely to achieve over 90% accuracy compared to other methodologies. The 90% confidence interval, (0.05, 2.05), sheds light on the potential range of odds ratios, capturing both lower and upper bounds in 90% of cases. In the 'Others' category, an odds ratio of 0.77 was determined, suggesting that papers in this category were 0.77 times less likely to achieve over 90% accuracy compared to other methodologies. The 90% confidence interval for this category ranged from (0.09, 6.89). These findings are detailed in Table 1.

Table 1. Odds ratio and confidence intervals for fruit maturity estimation approaches with greater than 90% accuracy.

Approach	No. of papers	Papers with accuracy>90%	Odds ratio	Confidence Interval 90%
Machine Vision through mathematical modeling	14	11	2.75	(0.53, 14.33)
Spectroscopy	4	2	0.31	(0.05, 2.05)
Others	3	2	0.77	(0.09, 6.89)

To assess heterogeneity among categories, mean sample size and mean accuracy data were collected. Cochran's Q test, performed using MedCalc, yielded a Q statistic of 17.1953, with a corresponding p-value of 0.0002, which was below the predetermined significance level of 0.05. Consequently, the statistically significant Q statistic led to the rejection of the null hypothesis, indicating that the 3 approaches were not equally effective for fruit maturity estimation, in favor of the alternative hypothesis. Additionally, the I^2 statistic was utilized to quantify the degree of heterogeneity. An I^2 value of 88.37% was obtained, signifying that a substantial portion (88.37%) of the variability in effect sizes across the categories could be attributed to genuine heterogeneity, rather than sampling error or chance. The 95% confidence interval for I^2 ranged from 67.73% to 95.81%, further corroborating the significant heterogeneity observed across the categories. Detailed results from Cochran's Q test and I^2 statistic are provided in Table 3 and the relevant data used for the analysis is presented in Table 2.

Table 2. Heterogeneity Analysis Results for Categories in Terms of Mean Sample Size, and Mean Accuracy.

Category	Sample size	Accuracy (%)	95% CI	Fixed Weight (%)	Random Weight (%)
Machine vision using mathematical modeling	261	93.870	90.236 to 96.456	41.32	34.87
Spectroscopy	277	88.448	84.084 to 91.963	43.85	35.05
Others	93	77.419	67.578 to 85.446	14.83	30.08
Total (fixed effects)	631	89.392	86.730 to 91.680	100.00	100.00
Total (random effects)	631	87.542	78.640 to 94.303	100.00	100.00

Table 3. Results for Cochran's Q Test, and I-square Statistic.

Q	17.1953
DF	2
Significance level	P = 0.0002
I^2 (inconsistency)	88.37%
95% CI for I^2	67.73 to 95.81

To assess publication bias, Egger's and Begg's tests were applied to all 21 studies, and the data utilized for these tests are outlined in Table 4. A significance level of 0.05 was employed for both tests. In Egger's test, the intercept was employed to gauge the asymmetry in the funnel plot, indicating potential publication bias. For an intercept of 1.3143, a calculated p-value of 0.5642 was obtained, exceeding the assumed significance level of 0.05. Consequently, the hypothesis that there exists no strong evidence of publication bias was upheld, as the intercept was not statistically significant.In Begg's test, Kendall's tau was utilized to measure the association between effect size and variance, determining the presence of bias. A weak negative association was observed (Kendall's tau = -0.04831), prompting further investigation into its statistical significance. Upon calculation, the p-value was found to be 0.7593, surpassing the 0.05 significance threshold. Consequently, the obtained Kendall's tau was not statistically significant, reinforcing the conclusion that no strong evidence of publication bias existed among the studies-Results of both tests are presented in Table 5.

Comprehensive visual representations of the data can be found in Fig. 3, which includes both a forest plot and a funnel plot, aiding in the visualization of the findings presented in Table 4.

Table 5. Publication Bias Analysis Results using Egger's and Begg's Tests for 21 Studies.

Egger's test	
Intercept	1.3143
95% CI	-3.3730 to 6.0017
Significance level	P = 0.5642
Begg's test	
Kendall's Tau	-0.04831
Significance level	P = 0.7593

Discussion with research gaps and future scope

Upon reviewing the historical progression of techniques for fruit maturity classification, it was observed that spectroscopy and other spectrum techniques were introduced before the 2000's, while machine vision techniques gained popularity in the late 2000s, with the exception of image analysis, which preceded even spectrum techniques. Between 2000 and 2010, advancements in spectroscopy techniques and the utilization of machine vision, especially through deep learning and artificial intelligence, began. In the last decade, with the advancement in artificial intelligence, machine vision approaches have become more accessible and highly accurate for maturity detection.

Table 4. Meta-analysis data based on proportions.

Study	Sample size	Accuracy (%)	95% CI	Fixed Weight (%)	Random Weight (%)
Jaramillo-Acevedo *et al.* (48)	65	87.692	77.181 to 94.534	1.31	4.38
Luna *et al.* (49)	450	91.333	88.343 to 93.765	8.93	5.15
Mazen *et al.* (40)	300	97.667	95.252 to 99.057	5.96	5.07
Septiarini *et al.* (20)	240	98.333	95.788 to 99.544	4.77	5.01
Worasawate *et al.* (50)	120	89.167	82.187 to 94.104	2.40	4.76
Septiarini *et al.* (43)	160	92.500	87.266 to 96.065	3.19	4.88
Zhuang *et al.* (51)	120	99.167	95.444 to 99.979	2.40	4.76
Kheiralipour *et al.* (52)	160	93.750	88.807 to 96.962	3.19	4.88
Castro *et al.* (42)	925	85.838	83.423 to 88.022	18.33	5.23
Taofik *et al.* (53)	60	95.000	86.076 to 98.957	1.21	4.31
Khodabakhshian *et al.* (4)	450	87.778	84.390 to 90.658	8.93	5.15
Somton *et al.* (26)	72	94.444	86.382 to 98.466	1.45	4.45
Shabdin *et al.* (44)	60	45.000	32.122 to 58.388	1.21	4.31
Mohapatra *et al.* (54)	120	97.500	92.868 to 99.481	2.40	4.76
Gharaghani *et al.* (55)	80	91.250	82.799 to 96.409	1.60	4.52
Kanchanomai *et al.* (25)	29	93.103	77.234 to 99.154	0.59	3.61
Tiwari *et al.* (56)	559	78.891	75.270 to 82.203	11.09	5.18
Astrianda *et al.* (57)	70	95.714	87.982 to 99.107	1.41	4.43
Kipli *et al.* (58)	338	96.154	93.513 to 97.936	6.71	5.10
Elhariri *et al.* (59)	175	92.571	87.632 to 95.985	3.48	4.91
Azarmdel *et al.* (41)	477	99.161	97.867 to 99.771	9.46	5.16
Total (fixed effects)	5030	91.580	90.780 to 92.331	100.00	100.00
Total (random effects)	5030	92.002	88.437 to 94.958	100.00	100.00

Notably, this systematic review found a decline in popularity for acoustic methods after the late 2000's. After careful evaluation of studies, several significant research gaps were identified:

1) Most papers estimating fruit maturity relied on either machine vision-based approaches or spectroscopy-based approaches alone, which proved unreliable for industry standards in fruits classification according to their maturity.
2) Many studies used visual sensors like cameras or spectrometers for data acquisition which are sensitive to illumination conditions and background environment. This can lead to inconsistent results and pose significant challenge to practitioners.
3) Most machine vision techniques utilises Artificial Neural Networks (ANN) or Support Vector Machine (SVM) for classifying fruits. Choosing a classification algorithm is an important step. Thus, more alternatives with Convolutional Neural Networks (CNN) and K-Nearest Neighbours (KNN) can be utilised for further strengthening of research goals.
4) Majority of studies collected samples from singular source and were of a specific type. This reduced the quality of results and impacted the reliability of the approach.

To address these research gaps and enhance the reliability and applicability of the techniques, following points should be considered:

1) Integration of Multiple Approaches: Instead of relying on a single approach, combination of different techniques like in hyperspectral imaging can enhance the comprehensiveness and robustness of the technique.
2) Overcoming Sensory Limitations: Researchers can explore more methods to normalize factors affecting visual sensors. Techniques like Image pre-processing or calibration of the instrument can mitigate the impact of external factors.
3) Exploration of different algorithms: Beyond ANN or SVM models, exploring a wider range of models based on CNN or KNN can be explored to strengthen the research goals, as comparing and evaluating different algorithms can improvise the accuracy and robustness of a technique.
4) Diverse sample collection: Utilizing varied samples from diverse sources can enhance the robustness of techniques. This approach improves the dataset quality and refines the test results.

Conclusion

The odds ratio for the machine vision approach, specifically through mathematical modelling, provided the highest likelihood of obtaining a research article with over 90% accuracy, followed by other miscellaneous approaches and spectroscopy. Furthermore, significant heterogeneity was observed among the 3 approaches, with an I^2 of 88.37%, indicating genuine differences in performance rather than being attributed to sampling error or chance. Additionally, both Egger's and Begg's tests showed no strong evidence of publication bias in the collected literature. Table 1 summarizes that machine vision papers had a higher mean accuracy and confidence interval compared to the other 2 categories. Therefore, based on the meta-analysis, it is evident that the machine vision approach, employing mathematical modelling and deep learning algorithms, emerged as the most suitable and promising method for fruit maturity detection. Its greater predictive strength sets it apart from other methodologies.

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Authors contributions

All the authors contributed equally to conceptualisation of the work, interpretation, analysis, writing, reviewing and editing of the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

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References

1. Elmasry G, Kamruzzaman M, Sun DW, Allen P. Principles and applications of hyperspectral imaging in quality evaluation of agro-food products: A review. Critical Reviews in Food Science and Nutrition. 2012;52(11):999-1023. https://doi.org/10.1080/10408398.2010.543495
2. Matteoli S, Diani M, Massai R, Corsini G, Remorini D. A spectroscopy-based approach for automated nondestructive maturity grading of peach fruits. IEEE Sensors Journal. 2015;15(10):5455-64. https://doi.org/10.1109/JSEN.2015.2442337
3. Zhang B, Dai D, Huang J, Zhou J, Gui Q, Dai F. Influence of physical and biological variability and solution methods in fruit and vegetable quality nondestructive inspection by using imaging and near-infrared spectroscopy techniques: A review. Critical Reviews in Food Science and Nutrition. 2018;58(12):2099-118. https://doi.org/10.1080/10408398.2017.1300789
4. Khodabakhshian R, Emadi B. Application of Vis/SNIR hyperspectral imaging in ripeness classification of pear. International Journal of Food Properties. 2017;20(3):S3149-63. https://doi.org/10.1080/10942912.2017.1354022
5. Gupta AK, Medhi M, Chakraborty S, Yumnam M, Mishra P. Development of rapid and non-destructive technique for the determination of maturity indices of pomelo fruit (*Citrus grandis*). Food Measure. 2021;15:1463-74. https://doi.org/10.1007/s11694-020-00734-4

6. Magwaza LS, Tesfay SZ. A review of destructive and non-destructive methods for determining avocado fruit maturity. Food and Bioprocess Technology. 2015;8:1995-2011. https://doi.org/10.1007/s11947-015-1568-y

7. Ndou A, Tinyani PP, Slabbert RM, Sultanbawa Y, Sivakumar D. An integrated approach for harvesting Natal plum (*Carissa macrocarpa*) for quality and functional compounds related to maturity stages. Food Chemistry. 2019;293:499-510. https://doi.org/10.1016/j.foodchem.2019.04.102

8. Intaravanne Y, Sumriddetchkajorn S, Nukaew J. Cell phone-based two-dimensional spectral analysis for banana ripeness estimation. Sensors and Actuators B: Chemical. 2012;168:390-94. https://doi.org/10.1016/j.snb.2012.04.042

9. Zhang J, Wang J, Zheng C, Guo H, Shan F. Nondestructive evaluation of chinese cabbage quality using mechanical vibration response. Computers and Electronics in Agriculture. 2021;188:106317. https://doi.org/10.1016/j.compag.2021.106317

10. Hasanzadeh B, Abbaspour-Gilandeh Y, Soltani-Nazarloo A, Cruz-G´amez EDL, Hern´andez-Hern´andez JL, Mart´ınez-Arroyo M. Non-destructive measurement of quality parameters of apple fruit by using visible/near infrared spectroscopy and multivariate regression analysis. Sustainability. 2022;14:14918. https://doi.org/10.3390/su142214918

11. Tugnolo A, Giovenzana V, Beghi R, Grassi S, Alamprese C, Casson A, Casiraghi E, Guidetti R. A diagnostic visible/near infrared tool for a fully automated olive ripeness evaluation in a view of a simplified optical system. Computers and Electronics in Agriculture. 2021;180. https://doi.org/10.1016/j.compag.2020.105887

12. Pampuri A, Tugnolo A, Giovenzana V, Casson A, Guidetti R, Beghi R. Design of cost effective LED based prototypes for the evaluation of grape (*Vitis vinifera* L.) ripeness. Computers and Electronics in Agriculture. 2021;189:106381. https://doi.org/10.1016/j.compag.2021.106381

13. Huang X, Lv R, Wang S, Aheto JH, Dai C. Integration of computer vision and colorimetric sensor array for nondestructive detection of mango quality. Journal of Food Process Engineering. 2018;41(8):e12873. https://doi.org/10.1111/jfpe.12873

14. Ayllon MA, Cruz MJ, Mendoza JJ, Tomas MC. Detection of overall fruit maturity of local fruits using convolutional neural networks through image processing. Proceedings of the 2nd International Conference on Computing and Big Data. 2019. https://doi.org/10.1145/3366650.3366681

15. Surya Prabha D, Satheesh Kumar J. Assessment of banana fruit maturity by image processing technique. Journal of Food Science and Technology. 2015;52:1316-27. https://doi.org/10.1007/s13197-013-1188-3

16. Wong ZY, Chew WJ, Phang SK. Computer vision algorithm development for classification of palm fruit ripeness. AIP Conference Proceedings. 2020;2233(1). https://doi.org/10.1063/5.0002188

17. Rupanagudi SR, Ranjani BS, Nagaraj P, Bhat VG. A cost effective tomato maturity grading system using image processing for farmers. 2014 International Conference on Contemporary Computing and Informatics (IC3I) Mysore India. 2014;7-12. https://doi.org/10.1109/IC3I.2014.7019591

18. Srivastava S, Sadistap S. Data processing approaches and strategies for non-destructive fruits quality inspection and authentication: A review. Food Measure. 2018;12:2758-94. https://doi.org/10.1007/s11694-018-9893-2

19. Yue XQ, Shang ZY, Yang JY, Huang L, Wang YQ. A smart data-driven rapid method to recognize the strawberry maturity. Information Processing in Agriculture. 2020;7(4):575-84. https://doi.org/10.1016/j.inpa.2019.10.005

20. Septiarini A, Sunyoto A, Hamdani H, Kasim AA, Utaminingrum F, Hatta HR. Machine vision for the maturity classification of oil palm fresh fruit bunches based on colour and texture features. Scientia Horticulturae. 2021;286. https://doi.org/10.1016/j.scienta.2021.110245

21. Zhang D, Lee DJ, Tippetts BJ, Lillywhite KD. Date maturity and quality evaluation using color distribution analysis and back projection. Journal of Food Engineering. 2014;131:161-69. https://doi.org/10.1016/j.jfoodeng.2014.02.002

22. Ashari S, Yanris GJ, Purnama I. Oil palm fruit ripeness detection using deep learning. Sinkron: Jurnal Dan Penelitian Teknik Informatika. 2022;7(2):649-56. https://doi.org/10.33395/sinkron.v7i2.11420

23. Ali MM, Hashim N, Hamid ASA. Combination of laser-light backscattering imaging and computer vision for rapid determination of oil palm fresh fruit bunches maturity. Computers and Electronics in Agriculture. 2020;169. https://doi.org/10.1016/j.compag.2020.105235

24. Zhang M, Shen M, Li H, Zhang B, Zhang Z, Quan P, Ren X, Xing L, Zhao J. Modification of the effect of maturity variation on non-destructive detection of apple quality based on the compensation model. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy. 2022;267(2). https://doi.org/10.1016/j.saa.2021.120598

25. Kanchanomai C, Ohashi S, Naphrom D, Nemoto W, Maniwara P, Nakano K. Non-destructive analysis of Japanese table grape qualities using near-infrared spectroscopy. Horticulture, Environment and Biotechnology. 2020;61:725-33. https://doi.org/10.1007/s13580-020-00256-4

26. Somton W, Pathaveerat S, Terdwong Worakul A. Application of near infrared spectroscopy for indirect evaluation of "Monthong" durian maturity. International Journal of Food Properties.2015;18(6):1155-68. https://doi.org/10.1080/10942912.2014.891609

27. Minas IS, Blanco-Cipollone F, Sterle D. Accurate non-destructive prediction of peach fruit internal quality and physiological maturity with a single scan using near infrared spectroscopy. Food Chemistry. 2021;335. https://doi.org/10.1016/j.foodchem.2020.127626

28. Hameed K, Chai D, Rassau A. A comprehensive review of fruit and vegetable classification techniques. Image and Vision Computing. 2018;80:24-44. https://doi.org/10.1016/j.imavis.2018.09.016

29. Yildiz F, Ozdemir AT, Uluı¸sık S. Evaluation performance of ultrasonic testing on fruit quality determination. Journal of Food Quality. 2019. https://doi.org/10.1155/2019/6810865

30. Landahl S, Terry LA. Non-destructive discrimination of avocado fruit ripeness using laser Doppler vibrometry. Biosystems Engineering. 2020;194:251-60. https://doi.org/10.1016/j.biosystemseng.2020.04.001

31. Nyalala I, Okinda C, Nyalala L, Makange N, Chao Q, Chao L, Yousaf K, Chen K. Tomato volume and mass estimation using computer vision and machine learning algorithms: Cherry tomato model. Journal of Food Engineering. 2019;263:288-98. https://doi.org/10.1016/j.jfoodeng.2019.07.012

32. Ashtiani SHM, Rohani A, Aghkhani MH. Soft computing-based method for estimation of almond kernel mass from its shell features. Scientia Horticulturae. 2020;262. https://doi.org/10.1016/j.scienta.2019.109071

33. Ponce JM, Aquino A, Millan B, And´ujar JM. Automatic counting and individual size and mass estimation of olive-fruits through computer vision techniques. IEEE Access. 2019;7:59451-65. https://doi.org/10.1109/ACCESS.2019.2915169

34. Schulze K, Nagle M, Spreer W, Mahayothee B, M¨uller J. Development and assessment of different modeling approaches for size-mass estimation of mango fruits (*Mangifera indica* L., cv.'Nam Dok Mai'). Computers and Electronics in Agriculture. 2015;114:269-76. https://doi.org/10.1016/j.compag.2015.04.013
35. Vivek Venkatesh G, Iqbal SM, Gopal A, Ganesan D. Estimation of volume and mass of axi-symmetric fruits using image processing technique. International Journal of Food Properties. 2015;18(3):608-26. https://doi.org/10.1080/10942912.2013.831444
36. Concha-Meyer A, Eifert J, Wang H, Sanglay G. Volume estimation of strawberries, mushrooms and tomatoes with a machine vision system. International Journal of Food Properties. 2018;21 (1):1867-74. https://doi.org/10.1080/10942912.2018.1508156
37. Gokul PR, Raj S, Suriyamoorthi P. Estimation of volume and maturity of sweet lime fruit using image processing algorithm. International Conference on Communications and Signal Processing (ICCSP) Melmaruvathur India. 2015;1227-29. https://doi.org/10.1109/ICCSP.2015.7322703
38. UluiSik S, Yildiz F, Ozdemir AT. Image processing based machine vision system for tomato volume estimation. Electric Electronics, Computer Science, Biomedical Engineerings' Meeting (EBBT) Istanbul Turkey. 2018;1-4. https://doi.org/10.1109/EBBT.2018.8391460
39. Wan P, Toudeshki A, Tan H, Ehsani R. A methodology for fresh tomato maturity detection using computer vision. Computers and Electronics in Agriculture. 2018;146:43-50. https://doi.org/10.1016/j.compag.2018.01.011
40. Mazen FMA, Nashat AA. Ripeness classification of bananas using an artificial neural network. Arabian Journal for Science and Engineering. 2019;44:6901-10. https://doi.org/10.1007/s13369-018-03695-5
41. Azarmdel H, Jahanbakhshi A, Mohtasebi SS, Mu˜noz AR. Evaluation of image processing technique as an expert system in mulberry fruit grading based on ripeness level using artificial neural networks (ANNs) and support vector machine (SVM). Postharvest Biology and Technology. 2020;166. https://doi.org/10.1016/j.postharvbio.2020.111201
42. Castro W, Oblitas J, De-La-Torre M, Cotrina C, Baz´an K, Avila-George H. Classification of cape gooseberry fruit according to its level of ripeness using machine learning techniques and different color spaces. IEEE. 2019;7:27389-400. https://doi.org/10.1109/ACCESS.2019.2898223
43. Septiarini A, Hamdani H, Hatta HR, Kasim AA. Image-based processing for ripeness classification of oil palm fruit. 5th International Conference on Science in Information Technology (ICSITech) Yogyakarta Indonesia. 2019;23-26. https://doi.org/10.1109/ICSITech46713.2019.8987575
44. Shabdin MK, Shariff ARM, Johari MNA, Saat NK, Abbas Z. A study on the oil palm fresh fruit bunch (FFB) ripeness detection by using Hue, Saturation and Intensity (HSI) approach. IOP Conference Series: Earth and Environmental Science. 2016;37(1). https://doi.org/10.1088/1755-1315/37/1/012039
45. Alhamdan AM, Atia A. non-destructive method to predict Barhi dates quality at different stages of maturity utilising near-infrared (NIR) spectroscopy. International Journal of Food Properties. 2017;20(sup3):S2950-59. https://doi.org/10.1080/10942912.2017.1387794
46. Zhena OP, Hashima N, Maringgala B. Quality evaluation of mango using non-destructive approaches: A review. Journal of Agricultural and Food Engineering. 2020;1:0003. http://doi.org/10.37865/jafe.2020.0003
47. Lai JW, Ramli HR, Ismail LI, Wan Hasan WZ. Oil palm fresh fruit bunch ripeness detection methods: A systematic review. Agriculture.2023;13(1):156. https://doi.org/10.3390/agriculture13010156
48. Jaramillo-Acevedo CA, Choque-Valderrama WE, Guerrero-Alvarez GE, Meneses-Escobar CA. Hass avocado ripeness classification by mobile devices using digital image processing and ANN methods. International Journal of Food Engineering. 2020;16(12):20190161. https://doi.org/10.1515/ijfe-2019-0161
49. Luna RG, Dadios EP, Bandala AA, Vicerra RRP. Tomato growth stage monitoring for smart farm using deep transfer learning with machine learning-based maturity grading. AGRIVITA, Journal of Agricultural Science. 2020;42(1):24-36. http://doi.org/10.17503/agrivita.v42i1.2499
50. Worasawate D, Sakunasinha P, Chiangga S. Automatic classification of the ripeness stage of mango fruit using a machine learning approach. AgriEngineering. 2022;4:32-47. https://doi.org/10.3390/agriengineering4010003
51. Zhuang J, Hou C, Tang Y, He Y, Guo Q, Miao A, Zhong Z, Luo S. Assessment of external properties for identifying banana fruit maturity stages using optical imaging techniques. Sensors. 2019. https://doi.org/10.3390/s19132910
52. Kheiralipour K, Nadimi M, Paliwal J. Development of an intelligent imaging system for ripeness determination of wild pistachios. Sensors. 2022; 22:7134. https://doi.org/10.3390/s22197134
53. Taofik A, Ismail N, Gerhana YA, Komarujaman K, Ramdhani MA. Design of smart system to detect ripeness of tomato and chilli with new approach in data acquisition. IOP Conference Series: Materials Science and Engineering. IOP Publishing. 2018;288. https://doi.org/10.1088/1757-899X/288/1/012018
54. Mohapatra A, Shanmugasundaram S, Malmathanraj R. Grading of ripening stages of red banana using dielectric properties changes and image processing approach. Computers and Electronics in Agriculture. 2017;143:100-10. https://doi.org/10.1016/j.compag.2017.10.010
55. Gharaghani BN, Maghsoudi H, Mohammadi M. Ripeness detection of orange fruit using experimental and finite element modal analysis. Scientia Horticulturae. 2020;261:108958. https://doi.org/10.1016/j.scienta.2019.108958
56. Tiwari G, Slaughter DC, Cantwell M. Nondestructive maturity determination in green tomatoes using a handheld visible and near infrared instrument. Postharvest Biology and Technology. 2013;86:221-29. https://doi.org/10.1016/j.postharvbio.2013.07.009
57. Astrianda N, Mohamad FS. Ripeness identification of tomato using different colour models based on neural networklevenberg-Marquardt. World Applied Sciences Journal. 2017;35:57-61. http://dx.doi.org/10.5829/idosi/wasj.2017.57.61
58. Kipli K, Zen H, Sawawi M, Noor MSM, Julai N, Junaidi N, Razali MISM, Chin KL, Masra SMW. Image processing mobile application for Banana ripeness evaluation. International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA) Kuching Malaysia. 2018;1-5. https://doi.org/10.1109/ICASSDA.2018.8477600
59. Elhariri E, El-Bendary N, Fouad MMM, Plato˘s J, Hassanien AE, Hussein AMM. Multi-class SVM based classification approach for tomato ripeness, innovations in bio-inspired computing and applications. In Proceedings of the 4th International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2013. 2014;175-86. https://doi.org/10.1007/978-3-319-01781-5_17
60. Rani N, Bamel K, Shukla A, Singh N. Analysis of five mathematical models for crop yield prediction. South Asian Journal of Experimental Biology. 2022;12(1):46-54. https://doi.org/10.38150/sajeb.12(1).p46-54

61. amel K, Bamel JS, Rani N, Pathak SK, Gahlot S, Singh RN. Crop yield prediction using satellite remote sensing based methods. International Journal of Botany Studies. 2022;7(2):35-40. https://www.botanyjournals.com/archives/2022/vol7/issue2/7-1-125

62. Bamel K, Rani N, Gahlot S, Singh RN, Pathak SK, Shukla A, Singh N, Bamel JS. Current approaches and future perspectives in methods for crop yield estimation. Bulletin of Environment, Pharmacology and Life Sciences. 2022;Special Issue(1):243-47. https://bepls.com/special_issue(1)2022/37.pdf

63. Rani N, Bamel JS, Shukla A, Pathak SK, Singh RN, Singh N, Gahlot S, Garg S, Bamel K. Linear mathematical models for yield estimation of baby corn (*Zea mays* L.). Plant Science Today (accepted). 2023. https://doi.org/10.14719/pst.2618