Bulletin of Environment, Pharmacology and Life Sciences
Bull. Env. Pharmacol. Life Sci., Vol 13 [1] December 2023: 333-342

Online ISSN 2277-1808
Journal's URL:http://www.bepls.com
CODEN: BEPLAD

REVIEW ARTICLE **OPEN ACCESS**

Non-destructive Fruit Volume Estimation using Digital Image Processing Techniques: A Systematic Review

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ABSTRACT
The global fruit industry has experienced steady growth over the past decade driven by increased health benefits awareness and demand for organic produce. Thus, non-destructive fruit volume estimation is vital to provide a high-quality product at a fair price, maximise packaging usage, and minimise the transportation costs and spoilage risk due to overfilling. The field of digital image processing has wide-ranging applications in key technical disciplines, including remote sensing, medical imaging, encoding, etc. In addition to that, it is prevalent in grading systems for packing lines as it can precisely determine a fruit's volume and mass without compromising its quality. The present systematic review provides a thorough analysis of the existing literature on digital image processing techniques and the various algorithms used to evaluate their accuracy and applicability in estimating fruit volume by examining factors like uniformity, size, and shape of the fruit. We reviewed 56 full-text articles published between 2013 and 2023 for information on techniques for fruit volume estimation. As per our analysis, the techniques employed by researchers from multiple disciplines are from three major domains - model based, stereo based and deep learning. Upon scrutinizing their intricacies, we found that the most accurate techniques we came across incorporated the use of 2D projective images, kinect sensors and MVS (multi-view stereo) algorithm & mask R-CNN respectively for the three specified domains. Our study has the potential to assist stakeholders in recognising the advantages and drawbacks of current techniques, while also offering valuable comprehension on room for improvement to achieve efficient real time applications.
Keywords: *Volume Estimation, Modelling, Stereo vision, Deep Learning*

Received 18.10.2023 Revised 27.11.2023 Accepted 27.12.2023

INTRODUCTION

The global fruit industry has seen a steady rise in popularity as demand for fresh produce among the consumers grows [1-4]. Advancements in computer technology and AI have enabled the use of computer vision in agriculture [5,6]. The precise measurement of fruit volume plays a critical role in managing and coordinating various aspects of the fruit industry, such as sorting, yield estimation, quality inspection, predicting optimum harvest times, and optimising transportation and packaging costs [7-10]. Timely monitoring of fruit size and shape also helps in improving the quality and productivity of a farm [11,12]. Traditionally, volume of fruits is measured manually using water and gas displacement methods [13,14]. However, these methods are time-consuming, demanding a lot of human labour, and require specialist hardware [15-18]. With advancements in digital imaging techniques, non-destructive methods have emerged as a promising alternative for fruit volume estimation [19]. Significant efforts in application of computer vision technology for fruit volume estimation have led to many new advancements. Existing methods can be broadly classified under 3 approaches: Model based approach, Stereo based approach and Deep Learning based approach. For the model-based approach, the volume is calculated by registering fruit as an input image with a predefined 3D fruit model [20]. Various techniques based on Shape, Solid of Revolution, Conical Frustum, and Regression can be applied to estimate fruit volume [21,22]. For instance, Tri T. M. Huynh *et al* [23] estimated the volume of a sweet potato using chopped pyramid methodology with an accuracy of 96%; Rodrigo Méndez Perez et al [24] estimated fruit volume with 85% accuracy for non-symmetrical shapes and 94% accuracy for symmetrical shapes; Zayde Alçiçek *et al* [25] estimated volume of mussels on the basis of geometrical attributes by using cubic spline curve. The model achieved an R^2 of 0.97 indicating its fitness in predicting the volume; Tri Huynh et al [26] also created a model using a chopped pyramid to estimate volume of carrots and cucumbers with an R^2 of 0.9805 and 0.982 respectively. Despite notable advancements, model-based approaches still struggle in estimating volume of irregular fruits and need a pre-trained 3d model, which impacts both speed and overall cost-efficiency [27]. The insufficiencies of model based approach paved the way for stereo vision techniques which reconstructed the fruit surface using images from multiple cameras [28]. For instance, Dionisio Andújar *et al* [28] used light structured sensors like the Kinect, made by Microsoft Corporation for capturing depth images and converting them into a point cloud using its reference system. By analysing these depth points on the fruit's surface multiple geometric characteristics like perimeter, curvature, and volume were measured; Aníbal Concha-Meyer et al [29] used radial projection technique for creating a 3d wireframe model. Surface fitting and approximation techniques were then employed to estimate volume; Li *et al* [30] used BPNN and wireframe model to estimate volume of tomatoes obtaining an accuracy of 92.93% and 95.60% respectively; Nyalala *et al* [31] estimated volume of tomatoes by using depth image processing algorithm to obtain various 2d and 3d features which were further applied to 5 regression models namely, SVM (linear, quadratic, cubic, radial basis function) and Bayesian ANN. Out of these 5 models, RBF SVM and Bayesian-ANN outperformed the rest of the models achieving an average accuracy of 94% and 95% respectively; Dehais *et al* [32] introduced a novel concept of employing a two-view 3D reconstruction technique aimed at enhancing the processing speed. To extract the relative pose, they proposed a modified RANSAC algorithm. The experimental results demonstrated a percentage error ranging from 8.2 to 9.8%. This approach was evaluated on a diverse range of general food object items and showcased superior performance when compared to alternative stereo-based methodologies. In all of the above approaches, image processing tasks such as segmentation, depth analysis played a key role. So, with the emergence of neural networks and self-learning models, machine learning algorithms were used to carry out various tasks [20,33-34]. Saha *et al* [35] used neural networks to classify star fruit based on their ripeness using multiple deep learning algorithms like: Linear SVM, LDA, Quadratic SVM, SDA, and Fine KNN. Out of these, LDA outperformed the rest of the algorithms in classifying starfruit with 96.2% and 93.3% accuracy for calibration and validation respectively; Lüling *et al* [36] employed Mask R-CNN (region-based convolutional neural network) to estimate volume of cabbage fruit with a mean accuracy of 87%; Ziaratban *et al* [37]) used mathematical modeling with ANN (artificial neural network) to predict volume of golden apples. The proposed method achieved R^2 , RMSE and MAE of 0.99995, 0 0.6959, and 0.5908 respectively. Despite the substantial progress made in image-based fruit volume estimation, the methods still exhibit some limitation that challenge their effectiveness such as requiring a predefined fruit shape model, slow processing time due to computational restraints, issue of occlusion and greater human efforts in obtaining multiple images [27]. Hence, further research and development of these vision-based techniques would also aid in estimating mass [38-41] and ripeness of fruit [42-45] which play a crucial role commercially. This work is a systematic review on digital image analysis techniques for fruit volume estimation. It discusses different techniques under DIP, evaluate their predictive performances and identify their strengths and limitations in determining fruit volume. It also identifies a technique that is economical, requires less computational resources, and provides enough accuracy to be used in industries.

MATERIAL AND METHODS

Eligibility Criteria

In order to conduct a rigorous and comprehensive systematic review of high-quality research articles that align with the research questions and objectives, the following eligibility criteria has been developed:

Relevancy:

- The article must be relevant to the research question or topic of the systematic review.
- The title, abstract, or keywords should indicate relevance to the research question.

Duplicates:

- Excluded duplicate articles to ensure each unique study is included only once.
- Used appropriate software or manual techniques to identify and remove duplicates.

Publication Date:

- Included articles published between 2013 and 2023.

Language:

- Considered articles published in the English language only.

Publication Types:

- Excluded editorials, commentaries, letters, and other non-research article types.

Data extraction sources

The following databases, namely AGRICOLA, Scopus, Taylor & Francis, Web of Science, Google Scholar, Semantic Scholar, PubMed were thoroughly searched for relevant articles published between the years 2013 to 2023.

Search approach

Research papers related to fruit volume estimation using image processing were taken from different databases, maintaining their inclusion-exclusion criteria and their quality. PRISMA framework was applied as shown in Fig. 1 to finalise suitable papers for the systematic review.

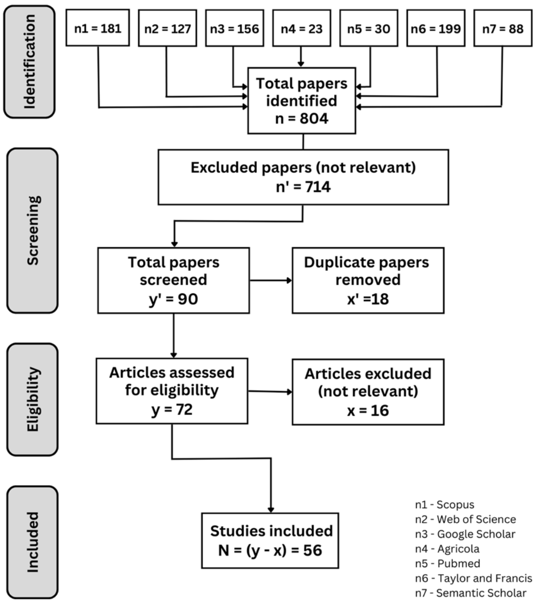


Fig. 1. PRISMA flowchart to find relevant papers for the systematic review

To conduct the relevant search process, the queries for different databases were generated from distinct combinations of the following keywords:

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

Selection Procedure

To ensure a rigorous and transparent selection process, the following steps were undertaken to identify relevant articles for inclusion in the systematic review:

Data Collation: A comprehensive search was conducted across multiple databases, including Web of Science, Taylor and Francis, AGRICOLA, PubMed, Scopus and Google Scholar. The search strategy incorporated relevant keywords and subject headings related to the research topic. All articles retrieved from these databases were compiled for further analysis.

Duplicate Removal: A thorough duplicate removal process was implemented to eliminate redundant articles. Google Sheets was employed to identify and exclude duplicates based on matching titles, authors, and publication details. In cases where software limitations were encountered, manual comparison and removal were performed.

Individual Filtering: The remaining articles were divided equally between five independent researchers to apply the developed eligibility criteria. Each researcher assessed the articles based on their titles and abstracts, examining their relevance to the research question. Any disagreements or uncertainties were resolved through discussions and consensus among the researchers. This systematic approach aimed to minimize bias and enhance the reliability of the final set of articles included in the systematic review.

Inclusion-Exclusion Criteria

Articles published between 2013 and 2023 and written only in English were selected. The Papers focusing on volume estimation of food through image processing were taken. Other papers that estimated volume through non image processing methods were excluded. Total number of collated data from the database stands at 804. Out of these, a screening on the basis of title and abstract was conducted, which resulted in the exclusion of 704 papers as they didn't provide enough information on the topic. The remaining 100 papers were then tested for duplicates and 18 papers were found to be duplicates of each other and hence removed. Finally, a complete assessment of the remaining 82 full text articles was conducted, and 16 papers were further excluded from the pool as they either used the same method or their full text was not available resulting in the pool count of 66 papers for the review.

Quality evaluation

To check the quality of collated papers following factors were considered:

Area of Interest: Paper focusing on food volume estimation were considered for our work.

Methodology: The paper must provide and focus on image-based approaches for food volume estimation.

Dataset: Detailed information of the dataset acquisition was searched and the diversity in the dataset was analysed.

Risk of Bias: In order to prevent any risk of bias, the screening procedure for collected literature was conducted by independent researchers. (To be improved)

Performance: Performance of a technique discussed in the paper was analysed on the basis of parameters used and the accuracy of their results.

BIBLIOMETRIC ANALYSIS

Analysis of publications using a geo chart.

The map in Fig. 2 displays multiple countries and their respective number of papers published. From the figure, it can be easily identified that research publications were found in almost every continent and Asian countries have produced the highest number in publication in this research field.

Analysis of publications by database.

Fig. 3. displays the percentage of literature gathered from various databases. With 48.2% papers obtained from Google Scholar followed by AGRICOLA and Semantic Scholar at 19.6% and 8.9% respectively.

Analysis on the basis of the most cited papers.

Fig. 4. displays the most cited papers in the form of a radar chart. It can be easily identified that [12] had the most citations standing at 224, followed by [44] and [17] with 171 and 139 citations respectively.

Analysis of papers published between 2014 - 2023.

Fig.5. displays the annual publication count of the fruit volume estimation using Model Based method, Deep learning and Stereo-vision method. As we can see in the figure, from 2015, researchers began delving further into this field and working on numerous studies in this field that ultimately culminated in publications. Consequently, between 2015 and 2023, the number of research articles increased significantly. The graph shown above depicts that the volume of research articles published in this discipline reached its peak in 2016.

Analysis by overall citations vs year.

Table 1 displays the overall citations from 2014 to 2023 in the area of our research field. From Fig.6., it can be clearly seen that most of the citations were made in the year 2016 showing a greater interest in the research of the topic in the said year.

Network analysis using keywords.

The map in Fig. 7 positions 112 keywords based on clustering algorithm allocated by VOS viewer software 1.6.18. The frequency of co-occurrence highlights the main keywords such as 'food volume estimation' and how the keywords are linked to each other within our field of study. The smallest occupancy is taken by the keyword 'review papers', signifying that less studies have been executed in this sector.

Network analysis of co-authors.

For network representation of co-authors in Fig.8., the type of analysis was co-authorship, which indicates relatedness on the basis of co-authored articles. Under this, the threshold of minimum documents was set to 3 and from a pool of 1057 authors 63 met the threshold. Out of these 63, the largest network of authors was 15 and is represented as follows:

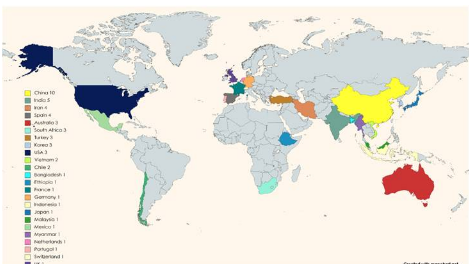


Fig. 2. Overall publications from different countries. different

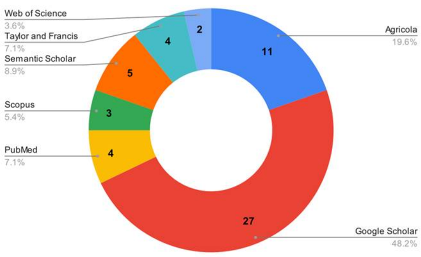
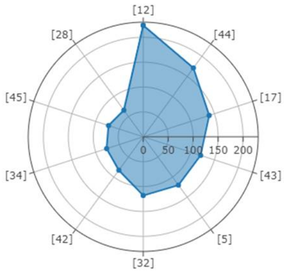


Fig. 3. Collected literature percentage from databases.



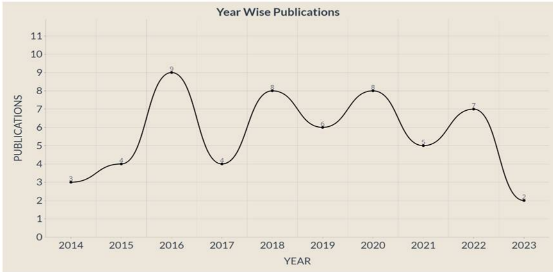


Fig. 4. Papers with highest citations. **Fig. 5. Overall papers published annually**

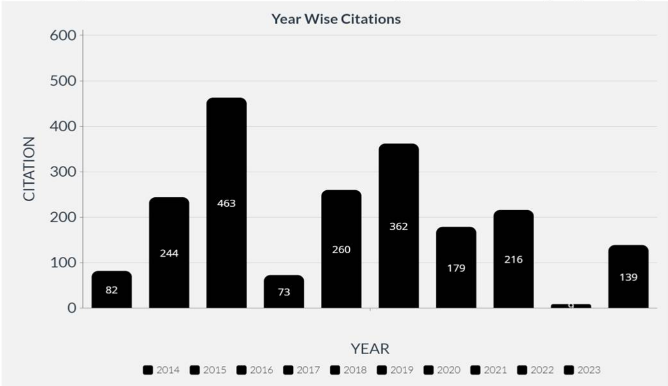


Fig. 6. Overall annual citations

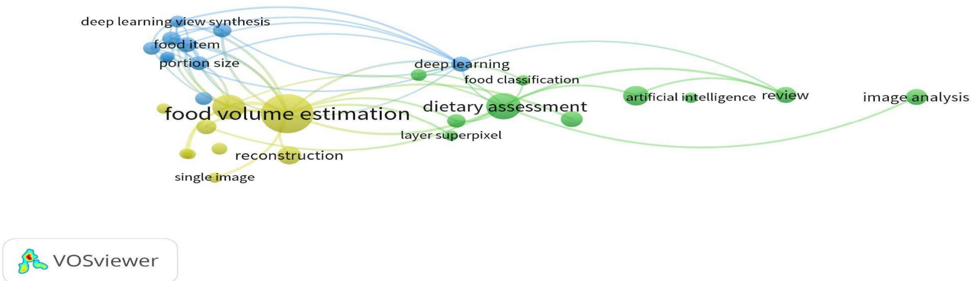


Fig. 7. Co-occurrence of keywords in various articles.

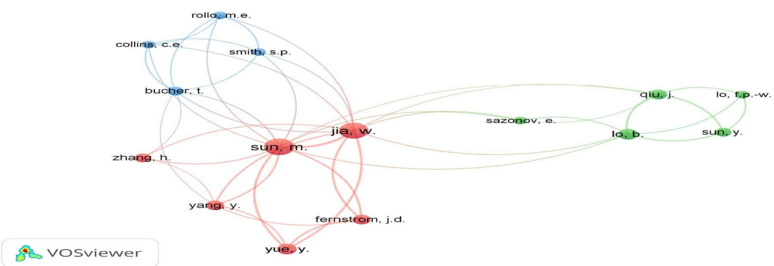


Fig. 8. Co-authorship of different articles

LITERATURE REVIEW

After a detailed analysis of the papers, the techniques used for volume estimation were classified into Model based, stereo based and Deep Learning based approaches. Based on the above classification details of most accurate technique are presented as follows:

Model Based techniques

Model based approaches involved capturing the image of the fruit from different angles. The image is then differentiated from its background using segmentation and thresholding. Many algorithms can be applied to obtain the boundaries of fruits. In 2017, Josh Chopin et al. [46] used Moore-Neighbor tracing algorithm to obtain the boundaries of the tomato fruit and proposed that segmented fruits and their boundary points can be used to calculate the average of upper and lower bounds of volume. The proposed approach estimated volume of high curvature fruits efficiently with an accuracy of 98% but gave significant error upto 11.9% for other general fruits.

Stereo based techniques

Andújar et al [28] proposed the use of depth cameras, specifically Kinect sensors, to estimate the ripeness and optimise the harvesting of cauliflower crops. Traditional hand-harvesting methods often result in reduced yields due to premature cutting. The Kinect Fusion algorithms enable the creation of accurate 3D models and point clouds of cauliflower plants. These models can determine the best time for individual fruit cutting, leading to improved harvesting efficiency and increased yields. The depth cameras showed high consistency with actual structural parameters, with less than 2 cm deviation in diameter/height and less than 0.6% overestimation in fruit volume. Additionally, leaf area measurements using Kinect sensors correlated with plant weight and area. However, leaf area index (LAI) did not prove to be a reliable indicator of final yield.

Deep Learning Techniques

Lüling et al [36], used a method for estimation of fruit volume and determination of Leaf-Area of cabbage for which 30 harvested cabbage plants were taken. The cabbage head's circumference was measured in order to calculate the fruit volume. They used a multi-view stereo (MVS) algorithm along with structure from motion (SFM) that used a set of 2-D images to estimate a 3D structure of a cabbage plant. Further, semantic segmentation and object identification techniques were combined in instance segmentation. Mask R-CNN with a Resnet-101 backbone was used to segment the cabbage head's area, thereby calculating the cabbage's volume with accuracy of 87%, based on ground truth data, attested to the proposed methodology's precision.

DISCUSSION

Analysis of papers according to different approaches

As per a detailed analysis of papers adopting a model-based approach, it can be seen from table 1 that the length of the fruit in various directions was the common parameter chosen in each paper.

Table 1- Papers adopting a model-based approach

Dataset	Results	Parameters used	References
Bananas: 18	Mean error for: length: 5.68%; Ventral straight length = 10.47%	Length, ventral height and arc height	[47]
Mussels: 35	R^2: 0.94	Area of cross section and length.	[25]
Potatoes: 233	Accuracy: 96%; R^2: 0.98	Height, minor and major diameter of the frustum.	[23]
Fruits/vegetables: 8 (Carrot, potato, tomato, orange, capsicum, lime, apple, pear); Objects: 8 (Sphere, cube, ellipsoid, bipyramid, cylinder, bicone, rectangular prism and triangular prism)	% Error for spherical and ellipsoidal shapes: 2%; % Error in general: 11.9%	Upper bound and lower bound	[46]
Potatoes: 52; Citrus fruits: 11; Tomatoes: 14	Accuracy for potatoes: 92.54%; Accuracy for citrus fruits: 88.82%; Accuracy for tomatoes: 89.02%	Height and width	[48]
Mangoes: 150	Accuracy: 96.8%	Length, width and thickness	[49]
Carrots: 191; Cucumbers: 160	R^2 for carrots: 0.9805; R^2 for cucumbers: 0.982	Height and diameter of top and bottom of frustum	[26]
Red Apples: 5; Green Apples: 6; Chilean Avocados: 5;Lemons: 6	Accuracy for symmetrical fruits: 95%; Accuracy for non-symmetrical fruits: 85%	Depth points of surface	[24]
Avocados: 360	R^2 : 0.93	Diameter and length	[50]
20 Apples: 20; Sweet Limes: 40; Lemons: 20; Oranges: 40	R^2 for Apples: 0.925; R^2 for Sweet Limes: 0.943; R^2 for Lemons: 0.910; R^2 for Oranges: 0.947	Eccentricity, equatorial diameter and polar diameter	[13]
Harumanis mangoes: 180	R^2: 0.9985	Length of major and minor axes	[51]
Pomegranates: 2	Accuracy: 92-96%	Surface area of fruit, seed, peel and arils	[52]

Table 2 - Detailed analysis of papers adopting stereo vision-based approach for comparison purposes

Dataset	Accuracy	Parameters used	Reference
Apple and soft drink can (6 iterations of experiment)	Accuracy: 83%	3D mesh of centroid and symmetrical points.	[53]
Mangoes: 600 (Totapuri, Badami, Kesar, Neelam)	Accuracy: 80%	Area, height and width of mango	[7]
Salad tomatoes:30; Roma tomatoes: 30; White button mushrooms: 35; Strawberries: 35	Coefficient of variation < 2%	3D model using boundary points	[29]
Tomatoes: 200	Accuracy: 92%	3D wireframe based on 2D coordinates and thickness of slice.	[30]
Clusters : 20	R^2: 0.77	Metric point cloud	[54]
Cauliflowers: 30	Accuracy: 96.30%	Width, length and maximum height	[28]

Table 3- Detailed analysis of papers adopting machine learning approach for comparison purposes.

Dataset	Results	Parameters used	References
Tomatoes: 300	R^2: 0.982	Area, perimeter, major axis, minor axis, eccentricity and radial distance	[55]
Food images: 1500	% Error: 11.6 - 20.1	Plate radius	[20]
Strawberries: 80	R^2: 0.8662	Weight, length, major axis and minor axis	[56]
Cabbage images: 600	Accuracy: 86.7%	Head radius and height	[36]
Golden apples: 100	R^2: 0.99995 RMSE: 0 0.6959 MAE: 0.5908	Major diameter, minor diameter and weight	[37]

Scope for Improvement and Future Prospects

To enhance the comprehensive and reliable understanding of fruit shape and size, the combination of different sensors like LiDAR or RGB-D cameras can be investigated. This approach can improve the robustness of volume calculation systems, especially in complex situations or for irregularly shaped fruits. Furthermore, real-time fruit quantity estimation systems are currently being developed, aiming for faster and continuous fruit classification and sorting by processing images or data streams in real-time. Expanding the fruit dataset to include a larger and more diverse range of varieties, sizes, and shapes is essential. This expansion will enable the generalisation and application of volume estimation techniques for different fruits, making them more widespread in the industry. Additionally, conducting calibration studies and error analysis becomes necessary to assess the accuracy and reliability of volume estimation methods in real-world situations. Integrating fruit quantity evaluation methods into automatic sorting and grading systems can lead to effective fruit grading. By evaluating both volume and quality simultaneously, fruits can be sorted based on their size and quality characteristics. This integration facilitates efficient fruit grading processes. Improving the robustness of volume estimation techniques requires employing adaptive thresholding, advanced image pre-processing, and robust extraction methods. These enhancements aim to address various environmental variations such as background noise, occlusions, and lighting conditions, thus improving the accuracy and reliability of volume estimation.

CONCLUSION AND RECOMMENDATIONS

In conclusion, the bibliometric analysis of the research field reveals several key findings. Firstly, Asian countries have emerged as the leading contributors in terms of publication output. Secondly, Google Scholar is the primary source for accessing research papers, followed by Semantic Scholar and Scopus. Furthermore, Koirala et al [12], 2019 stands out as the most cited paper with 224 citations, indicating its significant impact in the field. The analysis also highlights a substantial increase in the number of research articles between 2015 and 2023, with a peak in publications observed in 2020. Additionally, the year 2019

garnered the highest number of citations, indicating a heightened interest in the research topic. Lastly, the network analysis of coauthors identifies a pool of 63 authors who have collaborated on at least three publications, with the largest network consisting of 15 authors. These findings provide insights that indicate this research area is an active theme from 2015 and staying updated with the latest advancements in the field. After examining all the reviewed papers and techniques, it is evident that certain techniques such as model-based, thresholding, and contour analysis were utilised before the 2000s. In contrast, techniques like stereo vision and 3D scanning gained popularity in the late 2000s. The more recent advancements, including deep learning, machine learning, point cloud methods, and voxel-based methods, became prevalent after 2010. By organizing the techniques in chronological order, we can observe a clear pattern of technological advancement in volume estimation techniques for food products in the industry.
The literature review highlights the various techniques used for volume estimation, including model-based, stereo-based, and deep learning approaches. The model-based approach offers high accuracy but requires a pre-trained 3D model, impacting speed, cost-effectiveness, and processing time. The deep learning approach provides quick processing but may sacrifice accuracy. The stereo-vision approach reduces manual labour but presents challenges in technical implementation. The stereo vision approach has room for improvement, machine learning techniques overlook global serving style variations, and the focus on single object volume detection limits industrial application. Advancements in stereo vision and considering diverse serving styles are necessary to enhance these approaches' usability. Earlier, the authors have shown that various non-destructive techniques like mathematical modelling, satellite remote sensing and many others may be employed to predict the yield output and fruit maturity [57-61]. Likewise, stereo vision approach can be made economical as it requires less computational resources and provides enough accuracy to be used in industries, however, it is still in the developing phase.

REFERENCES

1. Lee, J., Nazki, H., Baek, J., Hong, Y., Lee, M., (2020). Artificial Intelligence Approach for Tomato Detection and Mass Estimation in Precision Agriculture. Sustainability. 12(21), 9138. https://doi.org/10.3390/su12219138
2. Arendse, E., Fawole, O.A., Opara U.L., (2014). Influence of storage temperature and duration on postharvest physico-chemical and mechanical properties of pomegranate fruit and arils, CyTA. J. Food. 12(4), 389-398. https://doi.org/10.1080/19476337.2014.900114
3. Arendse, E., Fawole, O.A., Magwaza, L.S., Opara U.L., 2016. Non-destructive characterization and volume estimation of pomegranate fruit external and internal morphological fractions using X-ray computed tomography. J. Food Eng.186, 42-49. https://doi.org/10.1016/j.jfoodeng.2016.04.011
4. Arendse, E., Fawole, O.A., Magwaza, L.S., Opara, U.L., 2017. Non-destructive estimation of pomegranate juice content of intact fruit using X-ray computed tomography. in VII International Conference on Managing Quality in Chains (MQUIC2017) and II International Symposium on Ornamentals in 1201. 297-302. https://doi.org/10.17660/ActaHortic.2018.1201.40
5. Meenu, M., Kurade, C., Neelapu, B.C., Kalra, S., Ramaswamy, H.S., Yu, Y., 2021. A concise review on food quality assessment using digital image processing. Trends Food Sci. Tech.118, 106-124. https://doi.org/10.1016/j.tifs.2021.09.014
6. Julien, S., Sane, C.A.B., Borianne, P., Malezieux, E., Nordey, T., Normand, F., Diatta, P., Niang, Y., Faye, E., 2018 "Is machine learning efficient for mango yield estimation when used under heterogeneous field conditions?." In XXX International Horticultural Congress IHC 2018: VII Conference on Landscape and Urban Horticulture, IV Conference on 1279. 201-208. https://doi.org/10.17660/ActaHortic.2020.1279.30
7. Dhameliya, S., Kakadiya, J., Savant, R., 2016. Volume estimation of mango. Int. J. Comput. Appl. 143(12),1. https://doi.org/10.5120/ijca2016910056.
8. Mansuri, S.M., Gautam, P.V., Jain, D., Nickhil, C., Pramendra, 2022. Computer vision model for estimating the mass and volume of freshly harvested Thai apple ber (*Ziziphus mauritiana* L.) and its variation with storage days. Sci. Hortic, 305, https://doi.org/10.1016/j.scienta.2022.111436.
9. Tello, J., Cubero, S., Blasco, J., Tardaguila, J., Aleixos, N., Ibanez, J. 2016. Application of 2D and 3D image technologies to characterise morphological attributes of grapevine clusters. J. Sci. Food Agric. 96 (13), 4575-4583. https://doi.org/10.1002/jsfa.7675
10. Yildiz, F., Özdemir, A.T., Uluışık, S., 2019. Evaluation performance of ultrasonic testing on fruit quality determination. J. Food Qual. 2019, 1-7. https://doi.org/10.1155/2019/6810865
11. Basak, J.K., Paudel, B., Kim, N.E., Deb, N.C., Kaushalya Madhavi B.G., Kim, H.T. 2022. Non-Destructive Estimation of Fruit Weight of Strawberry Using Machine Learning Models. Agronomy. 12(10):2487. https://doi.org/10.3390/agronomy12102487
12. Koirala, A., Walsh, K.B., Wang, Z., McCarthy, C. 2019. Deep learning for real-time fruit detection and orchard fruit load estimation: benchmarking of 'MangoYOLO'. Precis. Agric. 20, 1107-1135. https://doi.org/10.1007/s11119-019-09642-0
13. Venkatesh, V.G., Md. Iqbal, S., Gopal, A., Ganesan, D. 2015. Estimation of Volume and Mass of Axi-Symmetric Fruits Using Image Processing Technique, Inter. J. Food Prop. 18:3, 608-626, https://doi.org/10.1080/10942912.2013.831444

14. Khoje S.A., Bodhe S. K. 2015. A Comprehensive Survey of Fruit Grading Systems for Tropical Fruits of Maharashtra, Critical Reviews in Food Science and Nutrition. 55 (12), 1658-1671. https://doi.org/10.1080 /10408398.2012.698662
15. Uluisik, S., Yildiz, F., Özdemir, A., 2018. Image processing-basedachine vision system for tomato volume estimation, in: IEEE 2018 Electric Electronics, Computer Science, Biomedical Engineering's' Meeting (EBBT). p.1. https://doi.org/10.1109/EBBT.2018.8391460
16. Victorino, G., Braga, R., Santos-Victor, J., Lopes, C. M., 2020. Yield components detection and image-based indicators for non-invasive grapevine yield prediction at different phenological phases. Oeno One. 54(4), 833-848. http://dx.doi.org/10.20870/oeno-one.2020.54.4.3616
17. Xiao, F., Wang, H., Li, Y., Cao, Y., Lv, X., Xu, G., 2023. Object Detection and Recognition Techniques Based on Digital Image Processing and Traditional Machine Learning for Fruit and Vegetable Harvesting Robots: An Overview and Review. Agronomy. 13(3):639. https://doi.org/10.3390/agronomy13030639
18. Wang, Z., Koirala, A., Walsh, K., Anderson, N., Verma, B., 2018. In Field Fruit Sizing Using A Smart Phone Application. Sensors. 18(10):3331. https://doi.org/10.3390/s18103331
19. Khojastehnazhand, M., Mohammadi, V., Minaei, S., 2019. Maturity detection and volume estimation of apricot using image processing technique. Sci. Hortic. 251, 247-251. https://doi.org/10.1016/j.scienta.2019.03.033
20. Yang, Z., Yu, H., Cao, S., Xu, Q., Yuan, D., Zhang, H., Jia, W., Mao, Z., Sun, M., 2021. Human-Mimetic Estimation of Food Volume from a Single-View RGB Image Using an AI System, Electronics 10 (13), 1556. https://doi.org/10.3390/electronics10131556
21. Fitriyah, H., 2022. Accuracy of Various Methods to Estimate Volume and Weight of Symmetrical and Non-Symmetrical Fruits using Computer Vision. J. ICT Res. Appl. 16(3), 210-225. https://doi.org/ 10.5614/itbj.ict.res.appl.2022.16.3.2
22. Fu, L., Sun, S., Li, R., Wang, S., 2016. Classification of Kiwifruit Grades Based on Fruit Shape Using a Single Camera. Sensors. 2016; 16(7):1012. https://doi.org/10.3390/s16071012
23. Huynh, T.T.M., TonThat, L., Dao S.V.T. (2022) A vision-based method to estimate volume and mass of fruit/vegetable: Case study of sweet potato, Int. J. Food Prop. 25(1), 717-732. https://doi.org/ 10.1080/10942912.2022.2057528
24. Perez, R.M., Cheein, F.A., Rosell-Polo, J.R., 2017. Flexible system of multiple RGB-D sensors for measuring and classifying fruits in agri-food Industry. Comput. Elect. Agric. 139, 231-242. https://doi.org /10.1016/j.compag.2017.05.014
25. Alçiçek Z., Balaban, M.O., 2014. Estimation of Whole Volume of Green Shelled Mussels using their Geometrical Attributes Obtained from Image Analysis, Int. J. Food Prop. 17:9, 1987-1997. https://doi.org/ 10.1080/ 10942912.2013.779699
26. Huynh, T., Tran, L., Dao, S., 2020. Real-Time Size and Mass Estimation of Slender Axi-Symmetric Fruit/Vegetable Using a Single Top View Image, Sensors 20(18), 5406. https://doi.org/10.3390/s20185406
27. Lo, F.P.-W., Sun, Y., Qiu, J., Lo, B., 2018. Food Volume Estimation Based on Deep Learning View Synthesis from a Single Depth Map. *Nutrients. 10,* 2005. https://doi.org/10.3390/nu10122005
28. Andújar, D., Ribeiro, A., Fernández-Quintanilla, C., Dorado, J., 2016. Using depth cameras to extract structural parameters to assess the growth state and yield of cauliflower crops, Comput. Elect. in Agric. 122, 67-73. https://doi.org/10.1016/j.compag.2016.01.018
29. Concha-Meyer, A., Eifert, J., Wang, H., Sanglay, G., 2018. Volume estimation of strawberries, mushrooms, and tomatoes with a machine vision system, Int. J. Food Prop. 21(1), 1867-1874. https://doi.org/10.1080/ 10942912.2018.1508156
30. Li, H., Sun, Q., Liu, S., Liu, L., Shi, Y., 2021. A Novel Tomato Volume Measurement Method based on Machine Vision, Tehnički vjesnik, 28 (5), 1674-1680. https://doi.org/10.17559/TV-20210616091307
31. Nyalala, I., Okinda, C., Nyalala, L., Makange, N., Chao, Q., Chao, L., Yousaf, K., Chen, K., 2019. Tomato volume and mass estimation using computer vision and machine learning algorithms: Cherry tomato model. J. Food Eng. 263, 288-298. https://doi.org/10.1016/j.jfoodeng.2019.07.012
32. Dehais, J., Anthimopoulos, M., Shevchik, S., Mougiakakou, S., 2017. Two-View 3D Reconstruction for Food Volume Estimation. IEEE Trans. Multimedia. 19 (5), 1090-1099. https://doi.org/10.1109/TMM.2016.2642792
33. Ni, j, Gao, J, Li, J, Yang, H, Hao Z, Han, H, 2021 E-AlexNet: quality evaluation of strawberrys based on machine learning. J Food Measure. 15, 4530-4541. https://doi.org/10.1007/s11694-021-01010-9
34. Dijk, A.D.J.V., Kootstra, G., Kruijer, W., Ridder, D., 2021. Machine learning in plant science and plant breeding, iScience. 24 (1), 101890. https://doi.org/10.1016/j.isci.2020.101890
35. Saha, K.K., Rahman, A., Md Moniruzzaman, Md Syduzzaman, Md Uddin, Z., Md Rahman, M., Md Ali, A., Riza, D.F.A., Md Oliver, M.H., 2023. Classification of starfruit maturity using smartphone-image and multivariate analysis, Journal of Agriculture and Food Research, 11, 100473, 4-5. https://doi.org/10.1016/j.jafr.2022.100473
36. Lüling, N., Reiser, D., Straub, J., Stana, A., Griepentrog, H.W., 2022. Fruit Volume and Leaf-Area Determination of Cabbage by a Neural-Network-Based Instance Segmentation for Different Growth Stages. Sensors 23, 129,6-11,15. https://doi.org/10.3390/s23010129
37. Ziaratban, A., Azadbakht M., Ghasemnezhad, A., 2017. Modeling of volume and surface area of apple from their geometric characteristics and artificial neural network, Int. J. Food Proper. 20:4, 762-768. https://doi.org/10.1080/10942912.2016.1180533

38. Utai, K., Nagle, M., Hämmerle, S., Spreer, W., Mahayothee, B., Müller, J., 2019. Mass estimation of mango fruits (Mangifera indica L., cv. 'Nam Dokmai') by linking image processing and artificial neural network, Eng. Agricul. Environ. and Food. 12(1), 103-110. https://doi.org/10.1016/j.eaef.2018.10.003
39. Ponce, J.M., Aquino, A., Millan, B., Andújar, J.M., 2019. Automatic Counting and Individual Size and Mass Estimation of Olive-Fruits Through Computer Vision Techniques. IEEE Access. 7, 59451-59465. https://doi.org/10.1109/ACCESS.2019.2915169
40. Bucio, F. J., Isaza, C., Gonzalez, E., De Paz, J. P. Z., Sierra, J. A. R., Rivera, E. K. A. Non-Destructive Post-Harvest Tomato Mass Estimation Model Based on Its Area via Computer Vision and Error Minimization Approaches. IEEE Access,10,100247-100256, 2022. https://doi.org/10.1109/ACCESS.2022.3203348
41. Phate, V. R., Malmathanraj, R., Palanisamy, P. 2019. Classification and weighing of sweet lime (*Citrus limetta*) for packaging using computer vision system. J. Food Meas. Charact. 13, 1451-1468. https://doi.org/10.1007/s11694-019-00061-3
42. Gao, Z., Shao, Y., Xuan, G., Wang, Y., Liu, Y., Han, X., 2020. Real-time hyperspectral imaging for the in-field estimation of strawberry ripeness with deep learning. Artif. Intell. Agric. 4, 31-38. https://doi.org/10.1016/j.aiia.2020.04.003
43. Mohammadi, V., Kheiralipour, K., Ghasemi-Varnamkhasti, M., 2015. Detecting maturity of persimmon fruit based on image processing technique, Scientia Hort.184, 123-128. https://doi.org/10.1016/j.scienta.2014.12.037
44. Zhang, C., Guo, C., Liu, F., Kong, W., He, W., Lou, B., 2016. Hyperspectral imaging analysis for ripeness evaluation of strawberry with support vector machine, J. Food Eng. 179,11-18. https://doi.org/10.1016/j.jfoodeng.2016.01.002
45. Habaragamuwa, H., Ogawa, Y., Suzuki, T., Shiigi, T., Ono, M., Kondo, N. 2018. Detecting greenhouse strawberries (mature and immature), using deep convolutional neural network. Eng. Agric. Environ.Food, 11(3), 127-138. https://doi.org/10.1016/j.eaef.2018.03.001
46. Chopin, J., Laga, H., Stanley J., Miklavcic, J., 2017. A new method for accurate, high-throughput volume estimation from three 2D projective images, International Journal of Food Properties, 20:10, 2344-2357, 2017, pp. 2345-2350. https://doi.org/10.1080/10942912.2016.1236814
47. Hu, M.H., Dong, Q.L., Malakar, P.K., Liu, B.L., Jaganathan, G.K., 2015. Determining Banana Size Based on Computer Vision. Int. J. Food Prop. 18:3, 508-520. https://doi.org/10.1080/10942912.2013.833223
48. Jana, S., Parekh, R., Sarkar, B., 2020. A De novo approach for automatic volume and mass estimation of fruits and vegetables, Optik. 200, 163443. https://doi.org/10.1016/j.ijleo.2019.163443
49. Mon, T., ZarAung, N., 2020. Vision based volume estimation method for automatic mango grading system, Biosys. Eng. 198, 338-349. https://doi.org/10.1016/j.biosystemseng.2020.08.021
50. Mokria, M., Gebrekirstos, A., Said, H., Hadgu, K., Hagazi, N., Dubale, W., Brauning, A., 2022. Volume estimation models for avocado fruit, PLoS ONE 17(2): e0263564,4-11. https://doi.org/10.1371/journal.pone.0263564
51. Ibrahim MF, Ahmad Sa'ad FS, Zakaria A, Md Shakaff AY. In-Line Sorting of Harumanis Mango Based on External Quality Using Visible Imaging. *Sensors*. 2016; 16(11):1753, 2016, pp.3-10.
52. Salmanizadeh, F., Nassiri, S.M., Jafari, A., Bagheri, M.H., 2015. Volume Estimation of Two Local Pomegranate Fruit (*Punica granatum* L.) Cultivars and Their Components Using Non-Destructive X-Ray Computed Tomography Technique, Int. J. Food Prop. 18:2, 439-455.https://doi.org/10.1080/10942912.2013.833521
53. Salmanizadeh, F., Nassiri, S.M., Jafari, A., Bagheri, M.H., 2015. Volume Estimation of Two Local Pomegranate Fruit (*Punica granatum* L.) Cultivars and Their Components Using Non-Destructive X-Ray Computed Tomography Technique, Int. J. Food Prop. 18:2, 439-455.https://doi.org/10.1080/10942912.2013.833521
54. Herrero-Huerta, M., González-Aguilera, D., Rodriguez-Gonzalvez, P., Hernández-López, D., 2015. Vineyard yield estimation by automatic 3D bunch modelling in field conditions, Comput. Electron. Agric. 110,17-26. https://doi.org/10.1016/j.compag.2014.10.003
55. Nyalala, I., Okinda, C., Chao, Q., Mecha, P., Korohou,T., Yi, Z., Nyalala, S., Jiayu, Z., Chao, L., Kunjie, C., 2021. Weight and volume estimation of single and occluded tomatoes using machine vision, Int. J. Food Prop. 24:1, 818-832.
56. Lee, D.H., Cho, Y., Choi, J.M., 2017. Strawberry volume estimation using smartphone image processing. Hort. Sci. Tech. 35, 6, 707-716.
57. Rani N., Bamel J.S., Shukla A., Pathak S.K., Singh R.N., Singh N., Gahlot S, Garg S., Bamel K. (2023a). Linear Mathematical Models for Yield Estimation of Baby Corn (Zea mays L.). Plant Sci. Today (accepted) https://doi.org/10.14719/pst.2618
58. Rani, N., Bamel, K., Shukla, A., & Singh, N. (2022). Analysis of Five Mathematical Models for Crop Yield Prediction. South Asian J Exp Biol 12(1):46-54
59. Rani N., Garg S., Bamel K., Bhatt V., Sharma S., Mishra S.K., Saini N., Saloni. (2023b). A systematic review and comparative meta-analysis of non-destructive fruit maturity detection techniques. Plant Sci. Today (accepted), https://doi.org/10.14719/pst.2844
60. Bamel, K., Bamel, J.S., Rani N., Pathak S.K., Gahlot, S. & Singh, R.N. (2022a). Crop yield prediction using satellite remote sensing based methods. Int. J. of Botany Stud, 7(2): 35-40.
61. Bamel, K., Rani, N., Gahlot, S. & Singh, R.N. and Pathak S.K., Bamel, J.S. (2022b). Current Approaches and Future Perspectives in Methods for Crop Yield Estimation, *Bulletin of Environment, Pharmacology and Life Sciences* (ISSN 0970-3586), special issue (1):243-247

CITATION OF THIS ARTICLE

Neetu R, Kiran B, Nitesh S, Sneha G, Raghav A N, Sourabh S and Ishita M. Non-destructive Fruit Volume Estimation using Digital Image Processing Techniques: A Systematic Review. Bull. Env. Pharmacol. Life Sci., Vol 13 [1] December 2023: 333-342