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Non-destructive Mathematical Modeling Techniques for Fruit Volume Estimation: A Systematic Review and Meta-analysis

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ABSTRACT

In the recent past, the global fruit industry has experienced incredible growth, fueled by growing per capita earnings and greater health consciousness for fresh produce. Fruit volume plays a key role in precise yield estimation, improving productivity, sorting and packaging. This systematic review accompanied by meta-analysis sheds light on the non-destructive techniques and algorithms used in the estimation of fruit volume through mathematical modeling. A total of 50 studies published between 2008 and 2023 were reviewed in this work in 2023 at Shivaji College (University of Delhi), Delhi. Reviewing the studies analytically, the modeling techniques adopted by researchers usually belonged to categories of either statistical modeling or geometric modeling. An I-square statistic of 88.48% was obtained in the heterogeneity analysis demonstrating the extreme diversity between the above categories. Egger's and Begg's tests were also performed for examining the presence of publication bias, however they did not turn up any compelling evidence of its occurrence. The comparison between different categories with their coefficient of determination (R^2) between estimated and actual volume was also established using effect measures like odds ratios, risk ratiosand weighted odds ratios while sensitivity analysis was performed to assess the changes in result. This study also elucidates the strengths and shortcomings of different non-destructive techniques while using statistical methods to identify the performance of individual studies and to find the most suitable approach for estimating fruit volume. The meta-analysis concluded that the studies following statistical approach offered better R^2 values as compared to other methodologies.

Key words: Geometric modeling, Statistical modeling, Machine learning, Fruit volume estimation, Systematic review, Meta-analysis.

Mathematical modeling is essential across research fields, allowing for better understanding and prediction of outcomes before they occur. This proactive approach leads to improved decision-making, enhanced crop productionand reduced risks of disasters and losses. In agriculture, which is crucial for human survival and national economies, mathematical models significantly aid in predicting yields, estimating volumes and analyzing key agricultural factors. Numerous studies in the literature demonstrate the impact of these models in agricultural research, highlighting their importance in developing effective strategies for sustainable farming and ensuring food security in an ever-changing environment. The study by Bakoglu *et al.* (2016) utilizes non-linear growth models, specifically Logistic, Bertalanffy and Gompertz, to determine the best predictive models for plant length, dry stem and dry leaf weight in various species of bitter vetch. Later, Karadavut *et al.* (2017) applied Logistic, Richards and Weibull growth models to assess the growth patterns of 14 bitter vetch genotypes, identifying Richards's model as the best fit for most genotypes, while highlighting significant variability due to Turkey's diverse climate and soil conditions. In a study, Karthiayani and Nithyalakshmi (2020) measured respiration rates of three mango varieties stored at different temperatures to develop a mathematical model for predicting metabolic activity during ripening and storage. In one notable study, Singh (2022) employed mathematical modeling using central composite design to optimize the performance of producer gas from mustard stalks in a dual fuel engine, assessing its emission impacts, particularly SO_2, under various operational conditions, addressing the issue of stubble burning in Punjab, India. Looking at the importance of mathematical modeling, this study reviews its applications within the fruit industry.

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The fruit industry is spreading its roots rapidly on a global scale, driven by heightened recognition of various health advantages linked to the consumption of different fruits (Mon and ZarAung, 2020). Consumers mainly prefer fruits that rate high based on visual appearances such as shape, color, size and surface texture (Kilic and Bozokalfa, 2022; Mokria *et al.,* 2022; Omid *et al.,* 2010; Salmanizadeh *et al.,* 2015; Vivek *et al.,* 2018). Determining the size, volume or mass of fruits holds significance for aligning with consumer preferences and other reasons, including identifying appropriate packaging materials for consistent fruit batches and creating commercial value (Birania *et al.,* 2022; Pathak *et al.,* 2020; Rosado *et al.,* 2022; Wang *et al.,* 2018). Manual grading is typical and demands significant labor and time, necessitates meticulous sample preparationand proves inadequate for instant grading and sorting on industry level as it is prone to human visual errors (Concha-Meyer *et al.,* 2018; Mon and ZarAung 2020; Oo and Aung, 2018). Hence, machine vision approaches have led to prominent development and automation in the packing lines over the past few decades (Lee *et al.,* 2017; Moreda *et al.,* 2009).

Mathematical modeling based approaches have emerged as promising ways for fruit volume estimation without fruit destruction and loss of crop yield (Lee *et al.,* 2017). These approaches are commonly geometric or statistical. While many others are based upon tomography (Arendse *et al.,* 2016) and laser scanning (Saha *et al.,* 2022). Recently, the authors have reviewed the importance of mathematical modeling for crop yield prediction (Bamel *et al.,* 2022; Rani *et al.,* 2022) and have adopted this approach for baby corn yield estimation (Rani *et al.,* 2023). Multiple geometric modeling methods accompanied by vision based techniques have been used to estimate volume of fruits (Babic *et al.,* 2012; Huynh *et al.,* 2020; Huynh *et al.,* 2022). For instance, Venkatesh *et al.,* (2015) determined volume and mass of citrus fruits based on geometric diameters of the fruit samples and achieved an R^2 of 0.91 indicating a good accuracy. Alçiçek *et al.,* (2014) proposed a cubic splines approach to estimate green shelled mussels' volume with an R^2 of 0.97. Furthermore, Bozokalfa and Kilic (2010) adopted a mathematical model to determine the volume of peppers with an R^2 of 0.95. Various other geometric modeling techniques have also been used widely for fruit grading (Ibrahim *et al.,* 2016; Khojastehnazhand *et al.,* 2019) and yield estimation (Andújar *et al.,* 2016; Herrero-Huerta *et al.,* 2015).

Another popularly used modeling approach for non-destructive fruit volume estimation involves statistical modeling (Gongal *et al.,* 2019; Örnek and Kahramanli, 2018). For instance Nyalala *et al.* (2021) employed 7 different regression models to determine experimentally the volume of tomatoes having diverse shapes and sizes. This model achieved an R^2 of 0.98 which indicates a high accuracy. Saengrayup *et al.* (2009) used fruit dimensions as inputs for ANN (artificial neural networks) and regression models to estimate volume of plum fruits. An R^2 of 0.93 in this experiment showed that all these regression models were highly appropriate. Ziaratban *et al.* (2016) estimated the volume of apples with an R^2 of 0.99 using a model based on Levenberg-Marquardt algorithm and hyperbolic tangent sigmoid transfer functionFruit volume estimation has not only been restricted to geometric and statistical methods. In recent years, several other techniques in trend have been put to use. For instance, Keightley *et al.* (2010) used the tripod LiDAR method consisting of laser scan datasets for grapevine volume estimation with an R^2 of 0.93. Arendse *et al.* (2016) adopted X-ray computed tomography method to estimate pomegranate volume based on the size and number of voxels (3D pixels). Zheng *et al.* (2022) used UAV multispectral imagery and 6 different regression techniques for strawberry biomass prediction. The model created achieved an R^2 of 0.97. In addition to these, Li *et al.* (2015) used the approach of thermal and sunshine hours to determine apple fruit diameter and length with an R^2 of 0.88.

By conducting a systematic review of the existing literature and performing a meta-analysis, the objective is to provide a thorough examination of different non-destructive techniques utilised for fruit volume estimation. The discussed results will significantly contribute to the current knowledge baseand offer valuable insights to the researchers regarding the strengths and limitations of these techniques. This will stimulate advancements in the field, leading to improved agricultural practices and increased productivity levels (Bibwe *et al.,* 2022).

Selection criteria

The review work was conducted in 2023 at Shivaji College (University of Delhi), Delhi. Fig 1 highlights the selection parameters of research papers for the study. It depicts the eligibility criteria of selection (Fig 1a), information sources used for extraction (Fig 1b), various keywords (Fig 1c) and PRISMA methodology (Fig 1d) used for different queries for different databases.

Inclusion and exclusive criteria using prisma methodology

For inclusion in the systematic review and meta-analysis, papers that focused on fruit volume estimation through mathematical modeling techniques and written in the English language over the time frame of 2008-2023 were selected. At first, a total of 948 studies were selected from different databases out of which 849 papers were removed as they didn't clear the objectives of the systematic review and meta-analysis, leaving a total of 99 studies. Further, these studies were examined for any duplicates and hence 12 duplicates were removed. At last some papers were found to be using the same techniques as others while also not providing sufficient data for statistical analysis. Therefore, by removing 37 of such papers, a set of 50 full-text articles were left for the systematic review and meta-analysis.

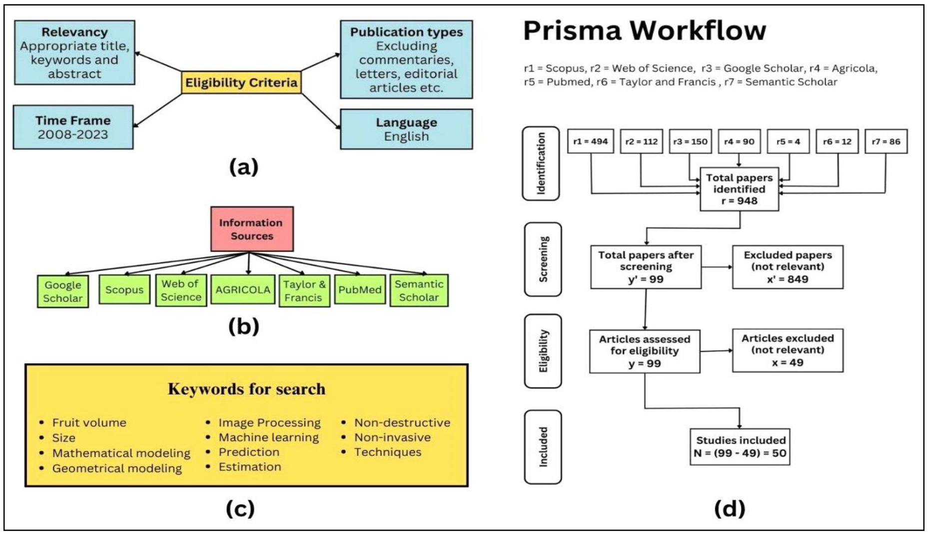

Fig 1: (a) Selection criteria based on various parameters (b) Different databases as information sources; (c) Keywords (d) PRISMA workflow diagram.

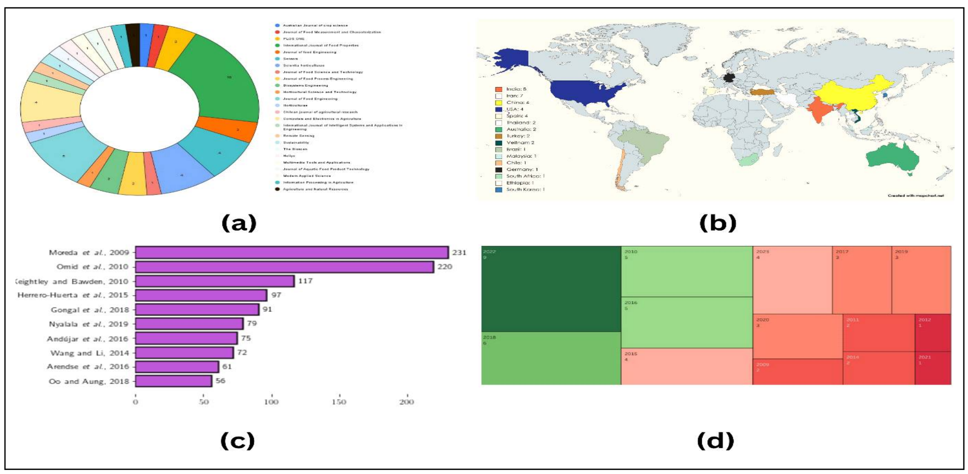

Fig 2: (a) Count of research articles by journal (b) Geo chart representing publications by countries (c) Most cited research articles (d) Number of annual publications .

Quality assessment

Quality of selected papers were measured through manual strategy based on the various factors such as area of interest which should lie around the mathematical modeling methods used for fruit volume estimation. Secondly the dataset was obtained from multiple sources and the third is the risk of biasness which was measured by different researchers individually and hence clarified.

Bibliometric analysis

Fig 2 depicts the bibliometric charts for collected literature. It shows the count of research articles by journal (Fig 2a), geo chart representing publications by countries (Fig 2b), most cited research articles (Fig 2c) and number of annual publications (Fig 2d). The following interpretations can be made on the basis of analysis:

- The International Journal of Food Properties ccounted for the greatest number of publications compared to other journals.
- Most of the publications originated from India followed by Iran and China.
- Moreda *et al.,* (2009) was the highest cited paper with 231 citations.
- 2022 had the greatest number of research articles published on fruit volume estimation techniques through mathematical modeling compared to any other year.

Literature review

There are many industries that require fruit volume estimation, including agriculture, food processing, storageand transportation. To optimize resource utilization and ensure quality in the production process, it has become increasingly important to develop accurate and non-destructive methods for estimating volume. In this literature review, we examine recent research on the volume estimation of fruits based on mathematical models, outlining their strengths and limitations, as well as possible future directions.

Background

A non-destructive approach for estimating the volume of fruits is offered by mathematical modeling, which does not require damage to the fruit to be done during measurement. To estimate fruit volume accurately, several mathematical modeling methods have been developed. A few common non-destructive methods for estimating fruits' volume along with their timelines are presented in the Table 1 below to provide a background of mathematical modeling evolution: The evolution of volume estimation methods for fruits using mathematical modeling shows a clear progression from simple geometric models to sophisticated and data-driven approaches. This field is expected to continue to develop as technology advances, with increased integration of machine learning and artificial intelligence, enhanced 3D scanning technologiesand the potential application of emerging technologies such as point cloud processing and augmented reality.

Contemporary research

Recent studies have focused on hybrid approaches, which combine different techniques, such as image processing and machine learning, to enhance accuracy and efficiency. Hybrid approaches take advantage of the strengths of different approaches to address the limitations of a single method. In Table 2 below, there are studies from 2023 that didn't use individual methods but demonstrate a combination of methods:

Hybrid models

Hybrid models that combine machine learning and artificial intelligence with enhanced 3D scanning technologies and the potential application of emerging technologies like point cloud processing and augmented reality, offer a powerful and versatile approach to volume estimation of fruits. However, they also have their strengths and limitations (Table 3).

Hybrid models are extremely promising as a method of estimating fruit volume, despite their limitations. Researchers are increasingly turning to hybrid models for accurate, efficientand nondestructive fruit volume estimation across a variety of industries as technology advances.

Statistical analysis

The following statistical analysis was conducted through MedCalc software version 22.009. Out of the 50 papers selected for literature review, 32 studies were screened on the basis of their sample size and correlation coefficient (which depicted the relationship between estimated and actual fruit volume in the studies).

Statistical analysis to assess heterogeneity between the categories

Based on the findings present in the existing literature, a test for heterogeneity among different categories was conducted to assess the inconsistency between the categories. Table 4 presents the characteristics of the

Table 1: Descriptions and timelines of mathematical models.

Mathematical models	Timeline	Description
Geometric models	Early 20th century	**Sphere-based Models:** A sphere is approximated as the fruit, to estimate a sphere's volume (Seyedabadi *et al.,* 2011). **Ellipsoid Models:** The volume of an ellipsoid fruit is calculated using three perpendicular axes (a, b, c) as follows: $V = 4/3\ \pi\ a\ \ b\ \ c$ (Anders *et al.,* 2019).
Weight and density models	Mid-20th century	The weight of the fruit is used to calculate the volume of the fruit based on its density (Nyalala *et al.,* 2021).
Regression models	Late 20th century	A regression model establishes a relationship between specific fruit dimensions and their volume (Seyedabadi *et al.,* 2011; Bibwe *et al.,* 2012; Kishor Kumar *et al.,* 2016, Saengrayup, 2009).
Image processing-based models	Late 20th century to early 21st century	**2D Imaging:** Fruit images are captured at different angles to calculate the projected area which is then integrated with height to give fruit volume (Chopin *et al.,* 2017). **3D Imaging:** Fruit surface and volume can be modeled with advanced 3D imaging techniques, *i.e* laser scanners and structured light systems (Anders *et al.,* 2019; Arendse, 2016).
Point cloud reconstruction	Early 21st century	Lasers or Time-of-Flight (ToF) cameras generate point clouds of a fruit's surface. Volume is calculated from the 3D reconstructed shape made by point clouds (Andújar *et al.,* 2016).
Statistical (Machine learning) based approaches	Developed since the 2010s	Datasets of fruit samples with known volumes can be used for training machine learning algorithms. Based on the features or images of new fruits, these models can estimate their volume (Nyalala *et al.,* 2021).

categories used for heterogeneity analysis. Table 5 presents the summary of the analysis results. The following interpretations can be made from the test results.

Cochran's Q test

After conducting the test between the categories, a very small significance level (P=0.0002) was obtained which is much smaller compared to the assumed significance level of 0.05. Therefore, it can be concluded that there is a significant difference between the correlation coefficient of these categories. The I^2 statistic is found to be 88.48%. It suggests that there is significant heterogeneity or true inconsistency between the categories.

This test clearly indicates the heterogeneity between the different categories. The test provides evidence for further investigation of the existing literature to identify the sources in order to improve the generalizability of the findings.

Statistical analysis to assess risk of bias between individual studies

Egger's and Begg's tests were conducted to identify the impact of any potential bias in the studies. Table 6 illustrates the characteristics of the data used. Table 7 provides a summary of these test results. Fig 3 illustrates the graphical representation of Table 7. The following interpretations can be made after analyzing the test results from Table 7.

Table 2: Hybrid models with parameters used and accuracy correlations from studies of 2023.

Studies	Hybrid models	Parameters used	Accuracy correlations
Steinbrener *et al.,* 2023	Image recognition + Deep learning	Simple RGB video frames; Inertial data	MAPE for untrained object: 16%
Saikumar *et al.,* 2023	Image processing + Regression modeling	Total phenolic content; Flavonoid; Antioxidant activity	Length-based model R^2: 0.924. Exponential models R^2: 0.950
Dalai *et al.,* 2023	3D reconstruction + Deep learning	Edge features taken from images	Accuracy: 98.59%, Precision: 98.21% MAPE: 6.1% RMSE: 0.93
Gené-Mola *et al.,* 2023	Deep learning + Modal and amodal segmentation	Modal mask; Amodal masks	MAE: 2.93 mm

Abbreviations used in Table 2: MAE (Mean absolute eror), RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error).

Table 3: Strength and limitations of hybrid models.

Strengths	Limitations
Accuracy: The 3D scanning technology provides precise and detailed spatial data while machine learning algorithms can learn complex patterns from large datasets.	**Data requirements:** Acquiring such data can be time-consuming and costly, especially for rare or specialized fruit varieties.
Robustness: Hybrid models are more robust when multiple methods are combined. A wide range of fruits can be processed with them, including those that have irregular shapes and sizes.	**Calibration and optimization:** It can be challenging to find the right balance between the various techniques to achieve the best results.
Automation: 3D scanning and machine learning technologies make volume estimation more efficient and reduce the need for manual intervention. In industrial settings and large-scale operations, this scalability is essential.	**Complexity:** Combining machine learning, 3D scanning technologies and emerging techniques like point cloud processing and augmented reality may involve intricate integration processes. Hybrid models can be hindered by this complexity.

Table 4: Data characteristics for heterogeneity analysis.

Approach	Mean sample size	Mean correlation coefficient	95% CI	Weight (%)	
				Fixed	Random
Geometric modeling	139	0.955	0.938 to 0.968	25.05	32.77
Statistical modeling	283	0.974	0.967 to 0.979	51.57	35.10
Others	130	0.940	0.916 to 0.957	23.39	32.52
Total (fixed effects)	552	0.963	0.957 to 0.969	100.00	100.00
Total (random effects)	552	0.959	0.932 to 0.975	100.00	100.00

Egger's test

Since the obtained significance level (P=0.6475) is greater than assumed significance level of 0.05. It can be concluded that there is no strong evidence of publication bias in the selected studies.

Begg's test

As the obtained significance level (P= 0.4049) is greater than the assumed significance level of 0.05. It can be concluded that there is no strong evidence of correlation between the effect sizes (correlation coefficient) and its variance. Thus, the effect size is not influenced by publication bias.

Table 5: Results of Cochran's Q test and I^2 test.

Q	17.3601
DF	2
Significance level	P = 0.0002
I^2 (inconsistency)	88.48%
95% CI for I^2	68.11 to 95.84

Table 6: Meta Analysis for individual studies.

Study	Sample size	Correlation coefficient (r)	95% CI	Weight (%)	
				Fixed	Random
Vivek Venkatesh *et al.,* 2015	17	0.954	0.874 to 0.984	0.26	2.80
Huynh *et al.,* 2022	233	0.990	0.987 to 0.992	4.22	3.22
Huynh *et al.,* 2020	351	0.990	0.988 to 0.992	6.38	3.23
Mokria *et al.,* 2022	360	0.964	0.956 to 0.971	6.54	3.23
Ibrahim *et al.,* 2016	180	0.999	0.999 to 0.999	3.24	3.21
Alçiçek and Balaban 2014	35	0.985	0.970 to 0.992	0.59	3.04
Herrero-Huerta *et al.,* 2015	20	0.878	0.711 to 0.951	0.31	2.87
Omid *et al.,* 2010	200	0.979	0.972 to 0.984	3.61	3.21
Babic *et al.,* 2012	30	0.889	0.777 to 0.946	0.49	3.00
Bozokalfa and Kilic 2010	45	0.952	0.913 to 0.973	0.77	3.09
Andújar *et al.,* 2016	30	0.930	0.857 to 0.966	0.49	3.00
Khojastehnazhand *et al.,* 2019	104	0.983	0.975 to 0.988	1.85	3.18
Khojastehnazhand *et al.,* 2010	25	0.973	0.938 to 0.988	0.40	2.95
Balaban *et al.,* 2011	151	0.993	0.991 to 0.995	2.71	3.20
Concha-Meyer *et al.,* 2018	100	0.960	0.941 to 0.973	1.78	3.18
Wang and Li, 2014	80	0.790	0.690 to 0.860	1.41	3.16
Fu *et al.,* 2016	490	0.990	0.988 to 0.992	8.93	3.24
Soltani *et al.,* 2010	50	0.987	0.977 to 0.993	0.86	3.10
Nyalala *et al.,* 2021	300	0.985	0.982 to 0.988	5.44	3.23
Saengrayup and Tansakul, 2009	575	0.964	0.958 to 0.969	10.48	3.24
Ziaratban *et al.,* 2016	100	1.000	1.000 to 1.000	1.78	3.18
Lee *et al.,* 2017	80	0.931	0.894 to 0.955	1.41	3.16
Örnek and Kahramanli, 2018	464	0.971	0.965 to 0.976	8.45	3.24
Nyalala *et al.,* 2019	300	0.985	0.981 to 0.988	5.44	3.23
Kishor Kumar *et al.,* 2016	300	0.973	0.966 to 0.978	5.44	3.23
Gongal *et al.,* 2018	150	0.98	0.972 to 0.985	2.69	3.21
Li *et al.,* 2015	20	0.942	0.857 to 0.977	0.31	2.87
Keightley and Bawden, 2010	36	0.930	0.866 to 0.964	0.60	3.04
Arendse *et al.,* 2016	23	0.894	0.764 to 0.955	0.37	2.92
Zheng *et al.,* 2022	532	0.985	0.982 to 0.987	9.70	3.24
Saha *et al.,* 2022	55	0.894	0.825 to 0.937	0.95	3.12
Cheepsomsong and Siriphanich, 2022	116	0.996	0.993 to 0.997	2.07	3.19
Total (fixed effects)	5552	0.984	0.983 to 0.985	100.00	100.00
Total (random effects)	5552	0.979	0.967 to 0.987	100.00	100.00

Table 7: Results for Egger's test and Begg's test.

Egger's test		Begg's test	
Intercept	-1.4571	Kendall's Tau	-0.1036
95% CI	-7.9006 to 4.9864	Significance level	P = 0.4049
Significance level	P = 0.6475		

Analysis of effect measures by odds ratio, weighted odds ratio, risk ratio for $R^2 < 0.95$

Odds ratio, weighted odds ratio and risk ratio were calculated for assessing the risk and odds of an approach to provide a study having an $R^2 < 95\%$. Table 8 presents the data for the effect measures. Table 9 presents the interpretation of these results.

Sensitivity analysis by weighted odds ratio and risk ratio

A sensitivity analysis of the collected literature based on different R^2 thresholds was conducted to improve the comprehensiveness of the statistical analysis and further analyze the results on the basis of risk ratio and weighted odds ratio for the selected literature. Table 10 presents the data characteristics of the sensitivity analysis. Following interpretations can be followed after analyzing the data obtained from Table 10.

Risk ratio

On the basis of Table 10, for almost all the thresholds the relative risk follows the same pattern where other methodologies have the highest risk followed by geometric modeling and statistical modeling respectively. So, we can conclude that the studies using statistical modeling present a lower risk compared to the other two approaches.

Weighted odds ratio

Weighted odds ratio also agreed with the risk ratio as statistical approaches offered a much lower odds ratio compared to othermethodologies for different thresholds of R^2.

Research gaps and future scope

The systematic review and meta-analysis provide valuable insight into the current state of fruit volume estimation research using mathematical modeling. The comprehensive analysis has nevertheless highlighted some research gaps that must be addressed. The following are the major research gaps identified.

Lack of standardization

The literature review revealed a wide variety of mathematical modeling approaches used for fruit volume estimation, but methodologies lack standardization. Inconsistent results can make it hard to compare findings among studies. Methods and reporting criteria should be standardized.

Insufficient focus on rare or specialized fruit varieties

Research on rare or specialized fruit varieties is limited in the literature review, with most studies focusing on common fruits. Certain industries require volume estimation of such fruitsand thus more research is needed.

Limited consideration of external factors

Several external factors may affect fruit volume estimation, which was not considered in the literature review. Environmental conditions, fruit ripenessand storage conditions should be taken into account in models. In futureresearch, these external factors may be investigated and models may be developed to better estimate fruit volume.

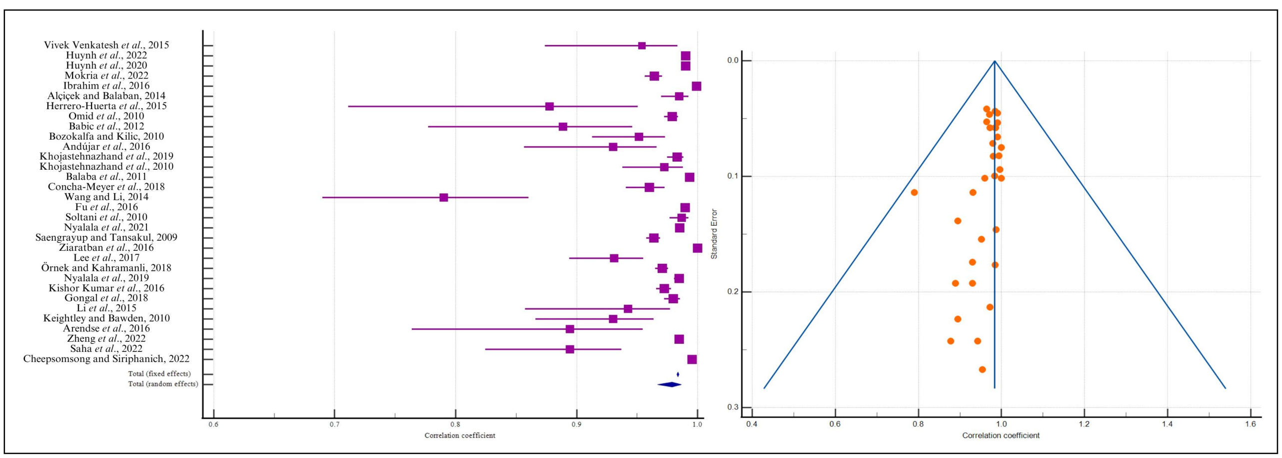

Fig 3: Forest plot (left) and Funnel plot (right) for bias assessment.

Table 8: Data characteristics of effect measures.

	Odds ratio	Weighted odds ratio	Risk ratio
Geometric modeling	0.75	0.964	0.8750
Statistical modeling	0.85	0.2805	0.9231
Others	2	0.462	1.33

Table 9: Interpretation of the effect measure.

Approach	Interpretation
Geometric modeling	The odds of a study using geometric modeling having an $R^2 < 0.95$ is 0.964 times lower compared to other studies.
	The risk of encountering a study using geometric modeling with an $R^2 < 0.95$ is 12.5% less compared to other techniques.
Statistical modeling	The odds of a study using statistical modeling having an $R^2 < 0.95$ is 0.2805 times lower compared to other studies.
	The risk of encountering a study using statistical modeling with an $R^2 < 0.95$ is 7.69% less compared to other techniques.
Others	The odds of a study using other methodologies having an $R^2 < 0.95$ is 0.462 times lower compared to other studies.
	The risk of encountering a study using other methodologies with an $R^2 < 0.95$ is 33% more compared to other techniques.

Table 10: Data characteristics for sensitivity analysis.

	Geometric modeling	Statistical modeling	Others
Risk ratio for $R^2 < 0.90$	0.622	0.375	3.47
Risk ratio for $R^2 < 0.92$	0.933	0.3	2.476
Risk ratio for $R^2 < 0.94$	1.04	0.5	1.73
Risk ratio for $R^2 < 0.96$	0.972	0.857	1.24
Risk ratio for $R^2 < 0.98$	0.8426	1.17	1.08
Weighted odds ratio for $R^2 < 0.90$	0.661	0.095	1.94
Weighted odds ratio for $R^2 < 0.92$	1.16	0.07	1.25
Weighted odds ratio for $R^2 < 0.94$	1.37	0.11	0.74
Weighted odds ratio for $R^2 < 0.96$	1.2	0.24	0.3956
Weighted odds ratio for $R^2 < 0.98$	0.557	0.78	0.346

Lack of real-time applications

Literature review studies mostly focused on offline fruit volume estimation. In industrial settings, mathematical modeling approaches should be explored in real-time fruit sorting and grading systems. Developing real-time solutions can boost productivity and reduce manual labor.

In future studies, future research can further enhance the accuracy, efficiencyand applicability of mathematical modeling approaches for fruit volume estimation by addressing these research gaps and exploring their scope areas, thereby improving agricultural practices and increasing fruit industry productivity.

CONCLUSION

The bibliometric analysis showed that 20% of the total papers were published in the International Journal of Food Properties. Further, India has produced the highest number of research papers in this domain and Moreda *et al.* (2009) was the highest cited paper with 231 citations between 2008 to 2024. Also, the year 2022 holds the highest number of publications. Many techniques which were relevant to mathematical modeling for volume estimation of fruit were found during this systematic review like geometric, weight and density, regression, point cloud and image processing with machine learning. Except image processing using machine learning techniques, all other techniques were introduced and majorly used in the 20th century. Many techniques were combined to form hybrid techniques to increase the efficiency and accuracy of estimation models, for example 3D imaging with deep learning.

Cochran's Q test conducted to find the inconsistency or heterogeneity between different categories provided statistically significant difference between correlation coefficient of different categories and thus showed an inconsistency of 88.48% between the categories. It also provided evidence that it is better to study different categories individually rather than combining all the studies. To check the impact of publication bias Egger's and Begg's test were conducted which provided no strong evidence of bias in collected literature. Effect measures like: odds ratio, weighted odds ratio and risk ratio were also calculated under sensitivity analysis which revealed that the techniques adopting statistical modeling approach had a lower risk of providing a smaller R^2 between estimated and actual volume compared to other approaches. Finally, certain gaps in the existing literature were also identified and addressed in the previous heading.

Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

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