PRECISION WEIGHT ESTIMATION MODEL FOR APPLE FRUIT USING IMAGE BASED REGRESSION ANALYSIS

Harshitha K M[1] , Akshatha Prabhu[1*] , N Shobha Rani[1] , Pushpa B. R[2]

Department of Computer Science, School of Computing, Mysuru Amrita Vishwa Vidyapeetham, India
Email: harshithakm9611@gmail.com ,p_akshathaprabhu06@gmail.com, n_shobharani@my.amrita.edu , pushpa@my.amrita.edu

Article History: **Received:** 18.04.2023 **Revised:** 07.05.2023 **Accepted:** 16.06.2023

Abstract: *The accurate estimation of apple weight is crucial for the apple industry as it is essential for quality control, grading, and pricing. Using image processing andsupervised learning approaches, this research attempts to develop a system for calculating the weight of apples. Theproposed method involves capturing images of 164 apples ,extracting features such as color and texture from the images, and using these features as input variables in a multilinear and K-NN regression model to predict the weight of the apple. The features computed from the images were analyzed using regression models, and the model's implementation was imposed using multiple metrics, such as R^2 score of .92 and .90 respectively achieved. The study's findings show that computer vision and machine learning have the ability to precisely estimatethe weight of apples, which could have implications for improving the efficiency and accuracy of apple sorting and packaging processes in the agriculture industry.*

Keywords: *Multilinear Regression (MLR), K-Nearest Neighbor Regression (K-NNR), R^2 (Coefficient of Determination), Positional Augmentation.*

DOI: 10.48047/ecb/2023.12.Si8.699

INTRODUCTION

Fruit weight calculation accuracy is critical in the fruit industry for grading, pricing, and quality control. Traditional methods of determining fruit weight necessitate intrusive, time-consuming, and labor-intensive physical measurements. Because of these constraints, novel, non- invasive, and effective methods for determining fruit weight must be developed. The expanding usage of supervised learning techniques and image processing has recently benefited a variety of areas, including agriculture and food production. These technologies provide a nonintrusive, rapid, and economical approach for a range of operations, including plant phenotyping, fruit detection, and quality evaluation [1]. The accurate prediction of fruit weight is strongly dependent on feature extraction in weight estimation. Size, shape, color, texture, and other exterior fruit properties can be obtained as attributes and used to estimate weight[2]. Fruit images can be processed to extract useful attributes such as color, size, and shape, which are important for determining fruit weight. These characteristics can then be applied to supervised learning approaches to produce predictive models that accurately estimate the fruit weight. The technique of calculating the weight of an apple for business or personal needs is known as apple weight estimation." Estimating an apple's weight is useful in a variety of situations, such as selling apples by weight, cooking or baking with apples, or simply keeping track of one's caloric intake. Traditional techniques of estimating apple weight entail physical measures that are time consuming, intrusive, and require professional personnel. These constraints have inspired the development of innovative, non-invasive, and efficient methods for estimating fruit weight. Image processing and supervised learning approaches have gained appeal in a variety of applications, including agriculture and food production, in recent years [3]. Image processing algorithms can extract valuable properties such as color, size, and form from fruit photos, which are required for weight estimation. Using a collection of fruit images and accompanying weight measurements, we train and validate our model. The proposed method has various advantages over current approaches, including the fact that it is non-invasive, quick, and inexpensive. Furthermore, our technology is adaptable to a variety of fruits and commodities, making it a versatile tool for the agriculture and food production industries. Image processing and supervised learning techniques have the potential to improve the accuracy and efficiency of fruit weight estimates, according to our findings, emphasizing the need to discover new solutions to the fruit industry's issues.

The proposed work consists of acquiring the dataset , performing data augmentation to increase the number of samples, followed by preprocessing , thresholding , feature extraction and applying regression models. The work is divided into following sections – Section II. Describes Related Work , section III. describes the proposed method that has the subsections – dataset collection , preprocessing ,segmentation , feature extraction. Section IV follows Results and Discussion and final section is Conclusion. The references are followed further.

RELATED WORK

[4] Regression analysis techniques were presented to model the link between the retrieved variables and the fruit mass. They used mean absolute error (MAE) and correlation coefficient (R) metrics to assess the performance of their suggested technique. The proposed method achieved an MAE of 9.12 and a R^2 of 0.92. [5] A method for determining the weight and volume of tomatoes. This study's dataset included both single and occluded tomatoes, allowing the authors to assess the resilience of their suggested technique to occlusions. The proposed method achieved an MAE of 8.34 and an R^2 value of 0.88 for single tomatoes and an MAE of

10.41 and an R^2 value of 0.86 for occluded tomatoes, according to the results.[6] suggests utilizing machine learning and metaheuristic techniques to classify and indirectly weigh sweet lime fruit. The execution of the suggested technique was evaluated using accuracy and MAE measurements. The proposed method attained an accuracy of

95.56 and an MAE of 3.56 for fruit categorization and an MAE of 7.24 for indirect weighing using PSO.[7] The method shown uses picture segmentation techniques to separate the oranges from their backdrop, and then 3D reconstruction techniques to estimate the volume of the oranges. The proposed technique achieved an MAE of 4.37g and an R2 value of 0.94 for size estimation, and 2.79 cm3 and an R2 value of 0.95 for volume estimation. [8] The goal was to create a non-destructive and accurate method for estimating mango weight from a single visible fruit surface using computer vision. According to the data, the SVR algorithm performed the best in mango weight estimation, with an MAE of 20.29. [9] The goal was to create a non-destructive and accurate method for estimating strawberry weight using machine learning models. According to the data, the RF algorithm performed the best in strawberry weight estimation, with an MAE of 1.44.[10] The destination of this research was to create a computer vision-based system for assessing apple volume and weight using 3D reconstruction and non-contact measuring methods. The results reveal that the suggested technique calculated the volume and weight of apples accurately, with mean absolute errors of 3.78 and 1.98 , respectively.[11] The proposed method generated a digital model of the sweet potato using a 3D reconstruction tool, which was then used to determine its volume and mass. The experiment used 50 sweet potatoes of varied sizes. The study's findings revealed that the vision based method was extremely accurate in measuring the volume and mass of sweet potatoes. Volume estimation had a MAE of 1.64, whereas mass estimation had a MAE of 2.08.[12] The proposed method analyses the weight of fish based on images using image processing techniques and machine learning algorithms. The study used images of 325 caught fish from ten different species. The findings of the study show that the proposed system was highly accurate in determining fish weight. The system has a MAE of 6.1 and a RMSE of 7.9. [13] Deep learning methods were used for object detection and segmentation, and a rule- based approach was used for weight estimation in the suggested system. The system achieved an overall mean intersection over union (IOU) score of 0.80 for segmentation and an object detection Map score of 0.89. The system could also estimate the weight of individual food products with an average error of

7.6 , which was much lower than older methods such as eye estimation.[14] The intent of this research was to create a method for determining item weight based on image analysis. The mean absolute error of the system was 4.2 , and the root mean square error was 5.9.[15] The goal of this work was to create a system for estimating wheat weight using image processing techniques. The study's findings revealed that the proposed system was extremely precise in determining the weight of wheat grains. The system had a 3.2 mean absolute error and a 4.1 root mean square error. [16] to estimate the weight of items based on images acquired by a top-view camera, the suggested system used image processing and machine learning methods. The system had a 4.6 g mean absolute error and a 6.1 root mean square error.[17] A deep learning algorithm was used in the suggested approach to estimate the weight of pigs based on Images captured by a camera positioned in the sow stall. The system's mean absolute error was 2.73 , while its root mean square error was 3.57. [18] The objective of this research was to create a machine-learning-based system for determining fetal weight at different gestational ages. The study used a dataset of 1,000 ultrasound images from women of various gestational ages. The system had a 6.2 mean absolute inaccuracy and a 7.8 root mean square error. [19] The goal of this research was to create a system Multiple linear regression is used to evaluate human weight based on body girth. Using image processing and machine learning methods, the suggested system predicts human weight based on body contour. According to the study's findings, the proposed approach was exceptionally accurate in predicting human weight from body silhouette. The mean absolute error of the system was 2.7 kg, while the root mean square error was 3.4 kg. These mistakes were far smaller than those achieved using established approaches such as BMI calculation and visual estimation.[20] The goal of this research was to create a system for dimensional analysis of items in a 2D image. Image processing methods were used in the suggested system to analyze items in a 2D image and extract dimensions such as length, width, and area. The system computed the area of objects with an average accuracy of 92% and extracted their length and width with an average accuracy of 95%.

From the above related work few of the observation found are:

1. Limited sample size.
2. Insufficient description of machine learning techniques.
3. Inadequate statistical analysis and comparison of other regression models .

PROPOSED METHOD

The overall workflow for apple weight estimation using machine learning and image processing is shown in Fig 1. Firstly, apple images are acquired, then data augmentation is done to increase the dataset and pre-processed by applying gaussian filter. Next segmentation is done to extract ROI using Otsu thresholding. Features are then extracted from the segmented fruit images. These features are used for multilinear and K-NN regression against the actual weight. Finally, the trained model is used to estimate the weight of new images. This approach offers a non-destructive and efficient way of estimating fruit weight, which can be useful in various applications, such as fruit sorting and quality control.

Dataset collection

The dataset utilized in this investigation contains 165 images of apple fruit. Before collecting the images, the weight of the fruits is physically measured by a weighting machine. The images were captured with a 48- megapixel Samsung A51 smartphone camera, which is equipped with an LED flash, ultra-wide camera has an aperture of f/2.2, the macro camera has an aperture of f/2.4 and ISO settings ranging from ISO 100 to ISO 3200 . To ensure consistency and remove background noise, the fruits were placed on a black background while capturing the images. The dataset contains a diverse set of fruit images, with variations in size, shape, texture, and color. The images were captured from various angles. The dataset was manually curated to remove any images with poor quality, blurriness, or misalignment. To evaluate the machine learning model's achievement, The dataset was separated into two parts: training contains 20% and testing contains 80% to prevent overfitting. The acquisition set up is as shown in Fig 1.The training set was utilized to extract picture attributes and train regression models. whereas the testing set was used to assess the model's accuracy in predicting fruit weight. Overall, this dataset is a significant resource for researchers and practitioners interested in developing machine learning-based algorithms for estimating the weight of fruits. Fig 2 shows the overall workflow of the proposed model.

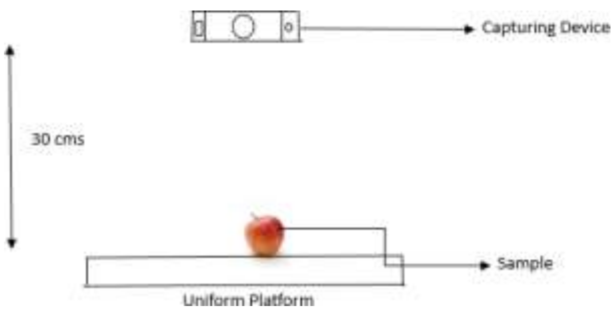


Fig 1. Image Acquisition setup

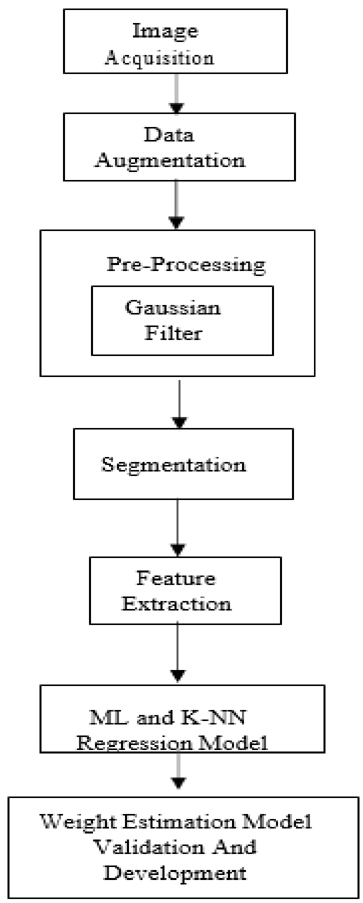


Fig 2. The suggested system's overall workflow

The act of creating new images from existing ones by applying various transformations or changes to the original images is referred to as "image data augmentation." This is often done in machine learning and deep learning applications to enhance the size of the training dataset and to improve the performance of the models. In this work, position augmentation is done.

Position augmentation

The use of numerous transformationsto the original images, such as rotation, translation, scaling, flipping, and shearing, can be used for position augmentation. As shown in Fig 3 (b) we have done horizontal flip, (c) and (d)done rotation to increase the size of dataset by manually using Resize pixel website. The sample images of apples are shownin Fig 3. The results after applying augmentation is as shownin Fig 4.

1) **Horizontal flip:** flip the image horizontally
2) **Rotation:** rotate the image by a certain angle

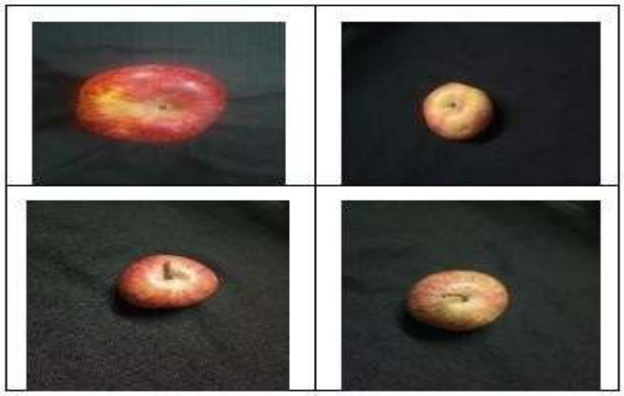


Fig 3. Images of Apple

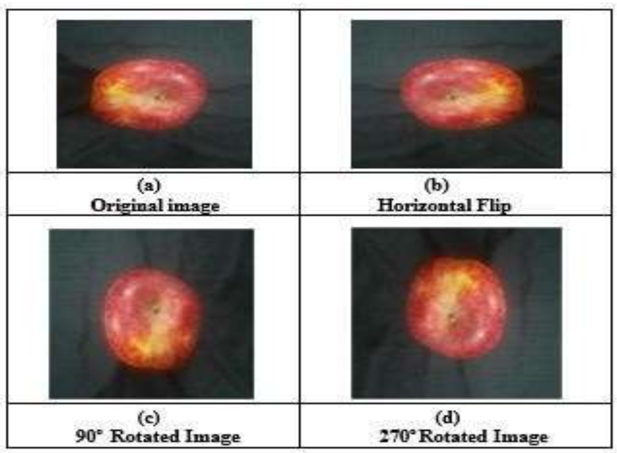


Fig 4. Augmented Images

Pre-processing

The pre-processing steps used for fruit image is gaussian filter. To smooth out images and reduce noise, Gaussian filtering is used. It accomplishes this by convolving the image with a Gaussian mask; it is a low-pass filter that emphasizes the edges and details of the image while minimizing noise.

Gaussian Filtering

Fig 5 shows images after applying gaussian gaussian filter applied. I order to smooth and to reduce noise in images , this method was employed. The image is convolved with a Gaussian function in order for Gaussian filtering to work. The Gaussian mask is a bell- shaped curve that distributes weights to image pixels based on their distance from the filter's center. Pixels closer to the center of the filterare given higher weights, while pixels farther away are given lower weights. By convolving the image with a Gaussian filter, high-frequency noise is reduced while preserving important features of the image, such as edges and corners. This can be useful for fruit weight estimation as it can help to reduce the impact of any noise or small variations in the image that might affect weight estimation accuracy. Gaussian filtering is a useful pre- processing technique that can be usedto reduce noise and smooth images, which can improve the accuracy of fruit weight estimation from images.

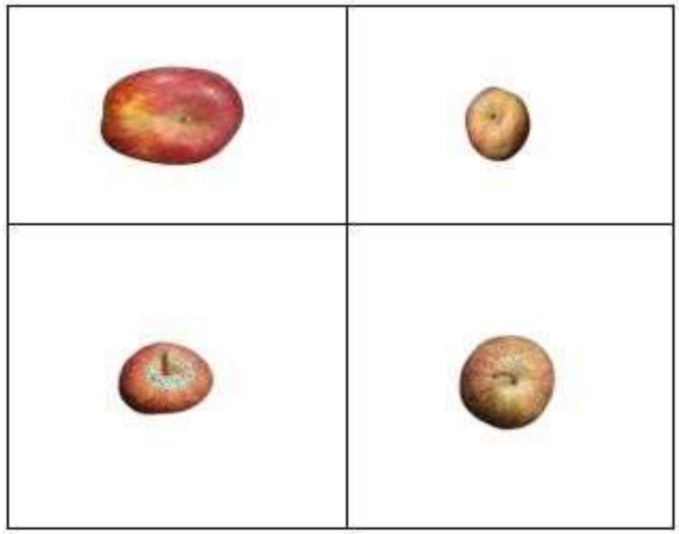


Fig 4. Gaussian filter applied images

Segmentation

Otsu thresholding: The ROI is extracted using Otsu thresholding . Otsu thresholding is a popular image processing technique that uses an appropriate threshold value to segment a image into ROI and background regions. The main idea behind Otsu's thresholding is to minimize the intra-class variance, which is the sum of the variances of the two classes weighted by their probabilities. In the context of fruit weight estimation, Otsu thresholding can be applied to binarize the grayscale fruit images, where the fruit pixels are separated distinct classes based on their intensity values. The threshold value is chosen to reduce intra-class variance while increasing inter-class variance, resulting in the optimum separation between the two classes. Fig 5 displays the images after applying Otsu thresholding for various samples.

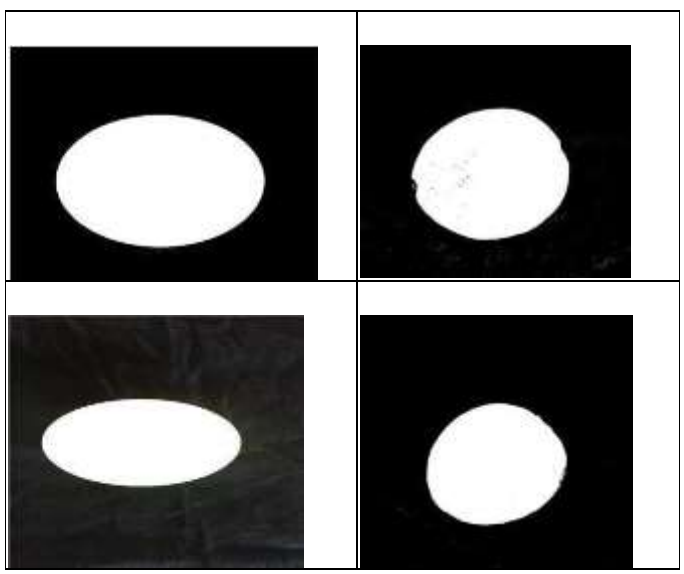


Fig 5. ROI extracted images

Feature Extraction

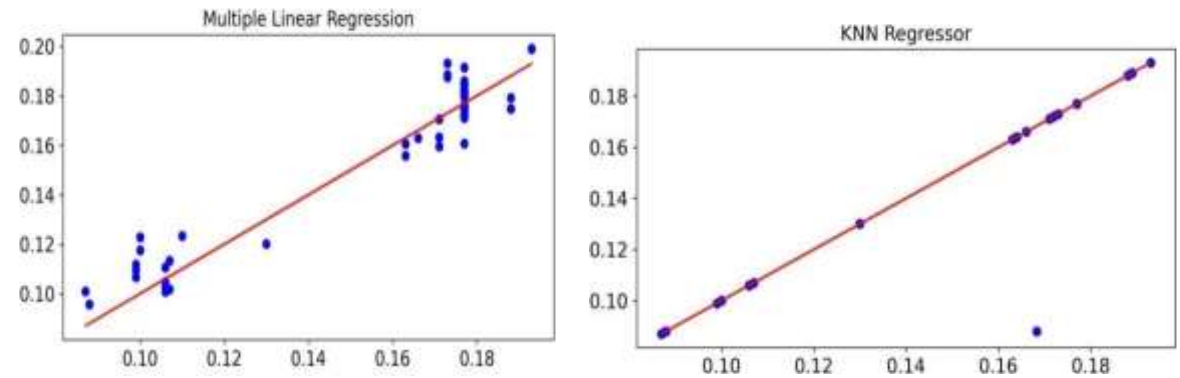
The feature extraction process involves analyzing eachsegmented image and extracting various statistical measurements that describe different aspects of the image. The color features are extracted from the image because it indicates ripeness of the fruits and the distance features are extracted to analyze the shape of the fruit. These measurements include the mean values and standard deviations of the color channels red, green, and blue extracted using the python built in function, as well as the area, major axis length, and minor axis length of the segmented object. In addition to these basic measurements, more advanced features such as eccentricity, entropy, and distance features are also calculated. 8 distance measures were calculated with an angle of 45° from the centroid of the fruit. Euclidean distance measure was used considering the centroid and the point on the circumference of the fruit boundary. Hence total of 8 distance measures were also considered in order to calculate the volume/ mass of the fruit. However, the distance measures vary at every angle from the centroid to the points on the boundary since the apple shape is not symmetrical. These features are combined in the feature vector that are further provided as input to the to train a machine learning model .. Table 1 describes the features, the equation used to represent them and the description about it.

Regression Model

The multiple linear and K-NN regressions graph for apple class shows the relationship between the features of the images and their actual weight is shown in Fig 6 (a) and (b)respectively. The graphs shows a line of best fit that represents the predicted weight of the fruits with the actual weights. The co-efficient of determination R^2 represents how well the datapoints match the actual line of fit. The value of R2 that ha value nearing to 1 indicates that there is a close match between the actual data and predicted data. The evaluation metrics of R2 of 0.92227 for MLR and 0.9072 for K-NN model where k=5 used to evaluate the model, an R2 of 9.272 for MLR model and 9.885 for K-NNR model respectively showed that the model performed well in predicting the weights of the apple. Table 2 shows the actual value and predicted value of apple in grams for MLR and K- NNR model. The

Table 1: Feature Description

Features Extracted	**Formula**	**Description**
Minor axis	minor_axis = $\sqrt{[(m2-m1)^2 + (n2-n1)^2]}$	End points (x1,y1) and (x2,y2) are found by computing the pixel distance between every combination of border pixels in the object boundary and finding pair with minimum value. The distance is measured as the length between minor axis endpoints.
Major axis	major_axis = $\sqrt{[(x2-x1)^2 + (y2-y1)^2]}$	End points (x1,y1) and (x2,y2) are found by computing the pixel distance between every combination of border pixels in the object boundary and finding pair with maximum value. The distance is measured as the length between major axis endpoints.
Eccentricity	Eccentricity = $\sqrt{1-\frac{b^2}{a^2}}$	a is the major axis length and b is the minor axis length.
Entropy	$Entropy = \sum p(x) \cdot \log 2\ p(x)$	p (x) is the likelihood of a specific intensity value x occurring in the image. The entropy value varies from 0 to $\log_2(n)$, where n is the image's total number of intensity levels. Entropy can be used as a feature to quantify the texture or complexity of an image region.
Distance features	d = $\sqrt{[(x2-x1)^2 + (y2-y1)^2]}$	D is the distance measure between the centroid (x1,y1) and co- ordinate on the boundary of the fruit region (x2,y2). The c- ordinates (x2,y2) are obtained by varying the radius form (x1,y1) at every 45°.



(a) **(b)**

Fig 6. a) MLR model scatter plot indicating the relationship between estimated and measured mass. (b) K-NN model scatter plot indicating relationship between estimated and measured mass.

Table 2: Actual and predicted weight of MLR and K-NNR Model

MLR Model		**K-NNR Model**	
Actual weight	**Predicted weight**	**Actual weight**	**Predicted weight**
0.163	0.160	0.130	0.130
0.171	0.162	0.189	0.180
0.177	0.180	0.177	0.177
0.177	0.185	0.164	0.164
0.177	0.184	0.088	0.088
0.163	0.159	0.177	0.175
0.173	0.191	0.130	0.130
0.177	0.184	0.177	0.175
0.110	0.125	0.163	0.163
0.177	0.171	0.106	0.106

CONCLUSION

The image processing and machine learning techniques applied to the dataset of Apple have shown promising results in accurately predicting their weights. The pre- processing Gaussian filtering technique is effective in enhancing the images for feature extraction. The extracted features such as RGB mean, standard deviation, area, major axis, minor axis, L count, A count, B count, eccentricity, entropy, and distance features were utilized to train and test the multiple linear and K-NN regression models. However, multiple linear was able to estimate precise weight of apple fruit by allowing to understand the impact of each feature on the actual weight The overall findings suggest that the combination of image processing and machine learning techniques can be utilized for accurate weight prediction of apple which can have applications in the agricultural and food industry. The proposed method achieved accuracy of 0.92 and 0.90 for MLR and KNN-regressor.

FUTURE ENHANCEMENT

In the future, more advanced and complex algorithms can be explored to further improve the accuracy of the fruit weight estimation. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are deep learning approaches that can be used to extract additional information and better grasp the patterns and correlations between image attributes and fruit weight. Furthermore, real-time fruit weight estimation can be developed by optimizing the algorithms for faster and more efficient processing. Finally, more types of fruits and vegetables can be added to the dataset to create a more comprehensive and diverse model.

REFERENCES

1. Shaikh, ashraf, asim sayyed, and mehvash shaikh. "Grading and Sorting Of Fruits Based On Image Processing." (2020).
2. G. Kumar and P. K. Bhatia, "A Detailed Review of Feature Extraction in Image Processing Systems," 2014 Fourth International Conference on Advanced Computing & Communication Technologies, Rohtak, India, 2014, pp. 512, doi: 10.1109/ACCT.2014.74.
3. Comert, Onur & Hekim, Mahmut & Adem, Kemal. (2017). Weight and Diameter Estimation Using Image Processing and Machine Learning Techniques on Apple Images. Uluslararası Muhendislik Arastirma ve Gelistirme Dergisi. 147-154. 10.29137/umagd.350588.
4. Rani, N Shobha & Murthy, Narayana & Sri, Arun & Laxmisagara, Vishwa & Srinath, Pavan & Madhusudan, Vinay. (2022). Mass estimation of citrus limetta using distance based hand crafted features and regression analysis. International Journal of Electrical and Computer Computer Engineering. 12. 3700-3708. 10.11591/ijece.v12i4.pp37003708.
5. Innocent Nyalala, Cedric Okinda, Qi Chao, Peter Mecha, Tchalla Korohou, Zuo Yi, Samuel Nyalala, Zhang Jiayu, Liu Chao & Chen Kunjie (2021) "Weight and volume estimation of single and occluded tomatoes using machine vision", International Journal of Food Properties,24:1, 818-832
6. Vikas R. Phate, R. Malmathanraj & P.Palanisamy (2021) Classification and Indirect Weighing of Sweet Lime Fruit through Machine Learning and Metaheuristic Approach, International Journal of Fruit Science, 21:1, 528545,
7. DOI: 10.1080/15538362.2021.1911745
8. Ifmalinda, R E Putri and I Rasinta "Estimation of Size, Volume and Weight of Oranges Using Digital Images Processing" , The open access IOPConference Series: Earth and Environmental Science, DOI 10.1088/1755- 1315/1059/1/012016
9. W. Aung, T. T. Thu, H. Thi Dar Aye, P. P. Htun and N. Zar Aung, "Weight Estimation of Mango from Single Visible Fruit Surface using Computer Vision," 2020 59th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE), Chiang Mai, Thailand, 2020, pp.366-371, doi: 10.23919/SICE48898.2020.9240422.
10. Basak, J.K.; Paudel, B.; Kim, N.E.; Deb, N.C.; Kaushalya Madhavi, B.G.; Kim, H.T. Non-Destructive Estimation of Fruit Weight of Strawberry Using Machine Learning Models. Agronomy **2022**, 12, 2487.
11. Baohua Zhang,[1]Ning Guo,[1]Jichao Huang,[1]Baoxing Gu,[1]and Jun Zhou Computer Vision Estimation of the Volume and Weight of Apples by Using 3D Reconstruction and Noncontact Measuring Methods,Journal of Sensors, doi:10.1155/2020/5053407
12. Tri T. M. Huynh, Long TonThat & Son V. T. Dao (2022) A vision- based method to estimate volume and mass of fruit/vegetable: Case study of sweet potato, International Journal of Food Properties, 25:1, 717-732, DOI: 10.1080/10942912.2022.2057528
13. Konovalov, Dmitry A., et al. "Automatic weight estimation of harvested fish from images." 2019 Digital image computing: Techniques and applications (DICTA). IEEE, 2019.
14. Y. He, C. Xu, N. Khanna, C. J. Boushey and E. J. Delp, "Food image analysis: Segmentation, identification and weight estimation," 2013 IEEE International Conference on Multimedia and Expo (ICME), San Jose, CA, USA, 2013, pp. 1-6, doi: 10.1109/ICME.2013.6607548.
15. Radhamadhab Dalai, Kishore Kumar Senapati "Weight Estimation through Image Analysis". International Journal of Computer Trends and Technology (IJCTT) V49(2):71-75, July 2017. ISSN:2231-2803. www.ijcttjournal.org. Published by Seventh Sense Research Group.
16. Sabanci, Kadir & Aydin, Cevat. (2016). Weight Estimation of Wheat by Using Image Processing

Techniques.Journal of Image and Graphics. 4. 10.18178/joig.4.1.51-54.
17. M. Mameli, M. Paolanti, N. Conci, F. Tessaro, E. Frontoni and P.Zingaretti, "Weight Estimation from an RGB-D camera in top-view configuration," 2020 25th International Conference on Pattern Recognition (ICPR), Milan, Italy, 2021, pp. 7715-7722,
18. doi 10.1109/ICPR48806.2021.9412519.
19. Y. Cang, H. He and Y. Qiao, "An Intelligent Pig Weights Estimate Method Based on Deep Learning in Sow Stall Environments," in IEEE Access, vol. 7, pp. 164867164875, 2019, doi: 10.1109/ACCESS.2019.2953099.
20. Chethana.C1, Dr. PreetiSavant2, "estimating fetal weight at varying gestational age using machine learning", International Research Journal of Engineering and Technology (IRJET)
21. H. Fitriyah and G. E. Setyawan, "Automatic Estimation of Human Weight From Body Silhouette Using Multiple Linear Regression," 2018 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Malang, Indonesia, 2018, pp. 749- 752, doi:10.1109/EECSI.2018.8752763.
22. A. S. Parihar, M. Gupta, V. Sikka and G. Kaur, "Dimensional analysis of objects in a 2D image," 2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Delhi, India, 2017, pp. 1-7, doi: 10.1109/ICCCNT.2017.8203937