

Original Research

Received 01 July 2026

Revised 09 Aug 2026

Accepted 22 Aug 2026

Natural Resources for Human
Health 2026, Vol. 6 (17s): 1504–1512

KEYWORDS:

Thermal imaging, defect detection,
machine learning, pomegranate

Thermal Imaging Based Defect Detection in Pomegranate with Machine Learning and Deep Learning Techniques

¹Ashvini Gaikwad, ²Manoj Deshpande, ³Varsha Bhole

¹Research Scholar, ²Professor, ³Associate Professor

^{1,2,3} A. C. Patil College of Engineering Kharghar

Navi Mumbai, Maharashtra, India

¹ashviniagaikwad@acpce.ac.in, ²mmdeshpande@acpce.ac.in, ³vybhole@acpce.ac.in

ABSTRACT: Fruits and vegetables are perishable goods and undergoes deterioration right from post-harvest. Fruit quality is determined by both internal and external factors, encompassing a wide range of physical, chemical and biological attributes that affect the appearance, taste, nutritional value, shelf life and market appeal of fruits. The internal factors are inherent characteristics are primarily governed by taste, aroma, texture, ripeness and nutritional composition whereas, the external factors of appearance, visual defects, size and shape. For evaluating the quality, internal as well as external characteristics need to be taken into account. The external characteristics can be assessed through RGB image processing techniques. The idea of internal characteristics can be obtained from the thermal image. In this paper, a machine learning and deep learning approaches are proposed for quality inspection of pomegranate with thermal imaging. A machine learning models are trained with KNN, SVM, Random Forest and CNN techniques for defect detection and classification of pomegranates in the categories of no defect, minor defect and major defect. The CNN approach outperforms with 92.78% accuracy as compared to 79.26% of SVM and 84.07% of random forest.

1. INTRODUCTION

Fruits and vegetables are prime sources of vitamins minerals and antioxidants for human being. The benefits of consuming fruit and vegetable are optimum when they are in their best condition or quality [2]. Fruits and vegetables are perishable agriculture goods and often go through various processes during post-harvest. In the supply chain, fruits and vegetables goes through the processes of sorting and quality inspection which is often done manually [2]. Accuracy of manual methods is questioned on the ability or skills, handling and the scale of work [3]. The implementation of automation in post-harvest and food handling processes offers a reliable means of overcoming these issues. At the primary stage the apparent attributes (colour, texture and size) of fruits are considered to be indicative parameters of the quality [4]. In an automatic inspection system, this attributes are processed with computer vision algorithms for inspecting the fruit quality [5].

With the computer vision, RGB image of fruit is taken and processed through a sequence of treatments of pre-processing, filtering, segmentation and classification [6]. Each step in this process is developed with dedicated algorithm for identifying and showcasing key features in the image [7]. Segmentation plays a critical role in defect detection by enabling precise identification and localization of defects within images. It divides an image into meaningful regions and isolates features or objects of interest. Segmentation allows for pixel-level localization of defects, enabling granular identification and isolation of even small or complex defects that bounding box-based methods might miss [8]. Based on the colour and defect machine vision and image processing techniques are used to assess quality of mangoes, ensuring consistency, efficiency and objectivity in post-harvest operations [9]. Segmentation techniques for defect detection in fruit vary in their approach, computational efficiency, robustness and accuracy [10]. K-means clustering is widely adopted for its simplicity and computational speed but is less robust in complex or noisy images. The Otsu's segmentation detects defects based on intensity thresholding [11]. The

colour segmentation divide images using colour space conversion (HSV or LAB) and are observed to be effective when defects have distinct colour characteristics [12]. The prediction model [13] and SVM classifiers are efficiency and accurate is defect detection with appropriate training. While the classical methods are useful for basic sorting and defects with strong visual cues, machine learning segmentation techniques have evolved for higher accuracy and generalization in modern fruit defect detection systems [14, 15 and 16].

The computer vision-based techniques rely on surface features and hence only surface defects are detected [17]. However, a fruit looking good at the surface may have internal spoilage, water core or insect infection. A variety of non-destructive testing techniques have been proposed by researchers for fruit quality inspection [18]. A comparative of digital and thermal imaging-based fruit defect detection technique [19] reveals that by deploying appropriate detection technique and segmentation method, accuracy and efficiency can be improved. The thermal image processing includes active and passive thermography. Passive thermography includes filtering, data compression, false colour contrast enhancement, histograms, and region of interest analysis. Active thermography includes transform methods of fast Fourier transform, wavelet transform and multispectral analysis for feature extraction and classification. In passive thermography statistical parameters of standard deviation and skewness are evaluated. For active thermography, the most common features used are the amplitude, phase, and frequency of the thermal signal [20]. K mean clustering, Grey level co-occurrence metrics (GLCM) and SVM are deployed [21] for detecting bruises in apple with thermal images. For feature extraction and classification, ANN, deep learning and machine learning algorithms have been recently worked out by many researchers with digital imaging. These algorithms are deployed for single fruit and hence opens a large scope of further research in this field [22]. Every material emits thermal radiations in proportion to the ambient temperature. The thermographic images clearly show the sub-surface defects in the material as these defective areas emit thermal radiations of different temperatures [23].

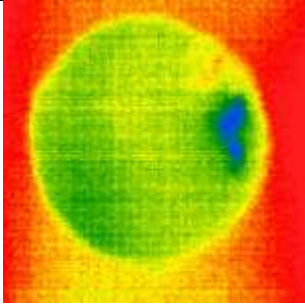
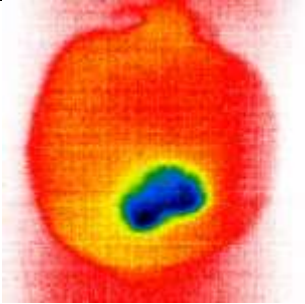
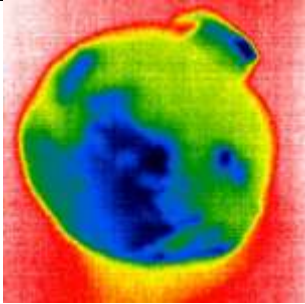
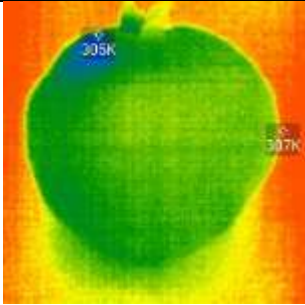
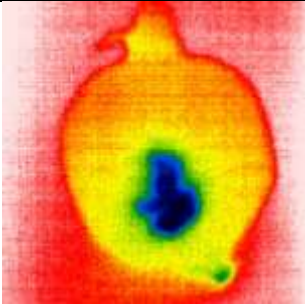
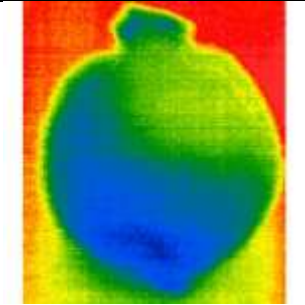
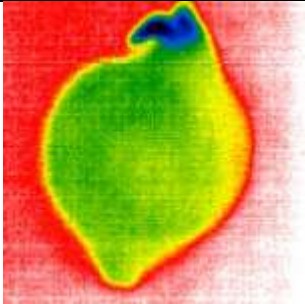
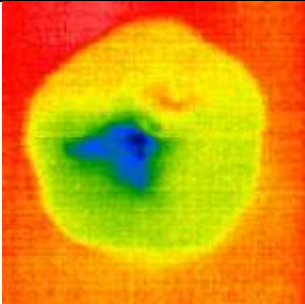
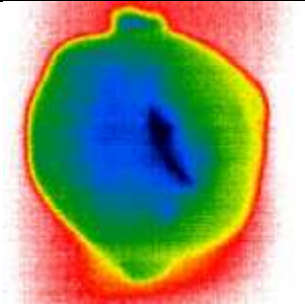
For bulk processing with thermal images, machine learning models are developed. These models are mainly deployed for digital images for fruit quality inspection. The fruit defect detection and grading has advanced through deep learning, machine learning and multispectral imaging techniques. A deep learning CNNs with data augmentation and transfer learning [24] accurately detects surface defects on green plums. A stacked sparse de-noising auto encoder and SVM classifier [25] improves postharvest fruit disease detection and grading. A machine learning framework combining visible and near-infrared spectroscopy for non-invasive quality assessment is proposed in [26] using sensor fusion. The fusion of spectroscopic data with machine learning models leads to high prediction accuracy. The transfer learning strategy learning with a lightweight MobileNetV3 architecture [27] to achieve effective apple defect detection suitable in real-time ensures that the model is adaptable to various apple cultivars and environments. Hyper-spectral techniques enable the detection of internal defects and prediction of shelf life, going far beyond what is possible with conventional RGB vision [28]. The multi-spectral imaging combined with machine learning emphasizes the advantage of multi-wavelength data for precise defect segmentation and classification [29]. A specialized optimized deep learning model for guava defect recognition overcomes the challenges related to irregular fruit shapes and surface textures [30].

The recent literature shows that the machine learning strategies are widely being adopted for defect detection in fruits and vegetable with digital imaging. For internal defect detection and quality assessment, machine learning models needs further investigation with thermal imaging. In this paper, GLCM feature extraction-based machine learning models are discussed for defect detection and classification of pomegranates with a pre-recorded dataset [31] of thermal images of pomegranate and comparative results are presented.

2. DEFECT DETECTION WITH MACHINE LEARNING

A fruit emits thermal radiations proportional to the difference between ambient temperature and internal temperature. The abnormalities in internal structure of fruit is reflected in terms of variations in thermal radiations as shown in Table 1.

Table 1: Sample thermal images of pomegranate in defect categories

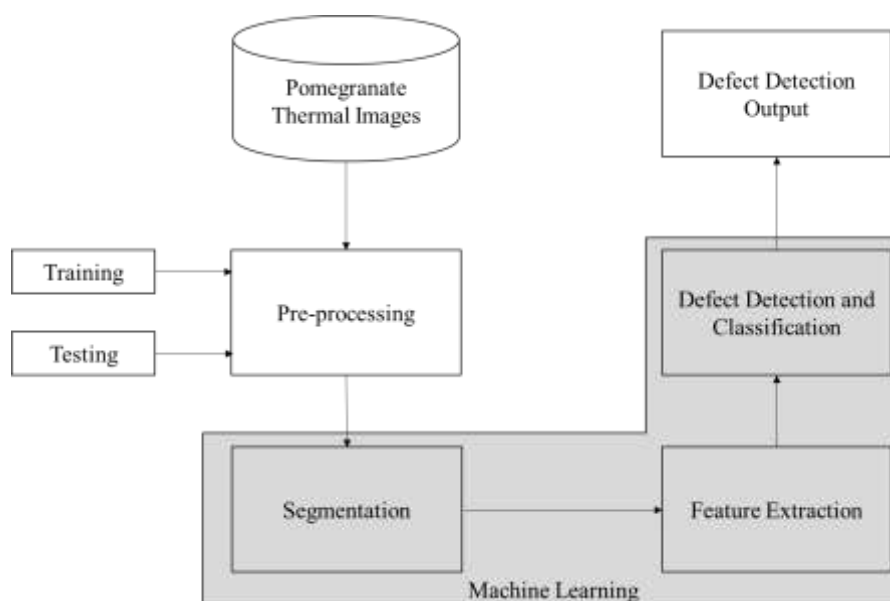
No defect	Minor defect	Major defect
		
		
		

2.1 Sample Collection

This data set of thermal images is pre-processed and all the images are of 256X256 pixel resolution. The data set is already labelled in three categories as no defect, miner defect and major defect. The sample images are shown in table 1. A user defined dataset is also added to increase the size of dataset. The total number of images used for experimentation are 2165, with over 600 thermal images in each category.

Table 2: dataset size

Class	no defect	Minor defect	Major defect
No. of images	651	746	768
Training	80%	80%	80%
Testing	20%	20%	20%



The dataset images are used to train a machine learning model for defect detection and classification. The general architecture of the machine learning model is shown in figure 1. Texture features are extracted using GLCM. The hyperparameter tuning of the SVM model is done by tuning the Regularization parameter and kernel coefficient with Radial Basis Function. The hyperparameter tuning in Random Forest is accomplished with setting 200 no. of trees. The tuned hyperparameters for CNN model are shown in table 3.

Table 3: Tuned hyperparameters of CNN Model

Hyperparameter	Value
Input Image Size	64 × 64 × 1 (Grayscale)
Number of Convolutional Layers	3
Filter Sizes	3 X 3
Number of Filters	16, 32, 64 (in each Convolution layer)
Pooling Type	Max Pooling (1st & 2nd), Average Pooling (3rd)
Activation Function	ReLU
Batch Normalization	After each Convolution layer
Fully Connected Layer Size	64 neurons
Output Layer	Softmax + Classification
Optimizer	Adam
Initial Learning Rate	0.001
Number of Epochs	40

3. RESULTS AND DISCUSSION

For defect detection and classification, 80% of the data is used for training and 20% data is used for testing. The classification accuracy at testing of SVM, KNN, Random forest and CNN model stands at 75.93%, 84.07% and 93.33% respectively. The

accuracy (A), precision (P), recall (R) and F1 scores in percentage for distinct defect categories identified from thermal images of pomegranate are mentioned in table 4. The average values are mentioned in table 5.

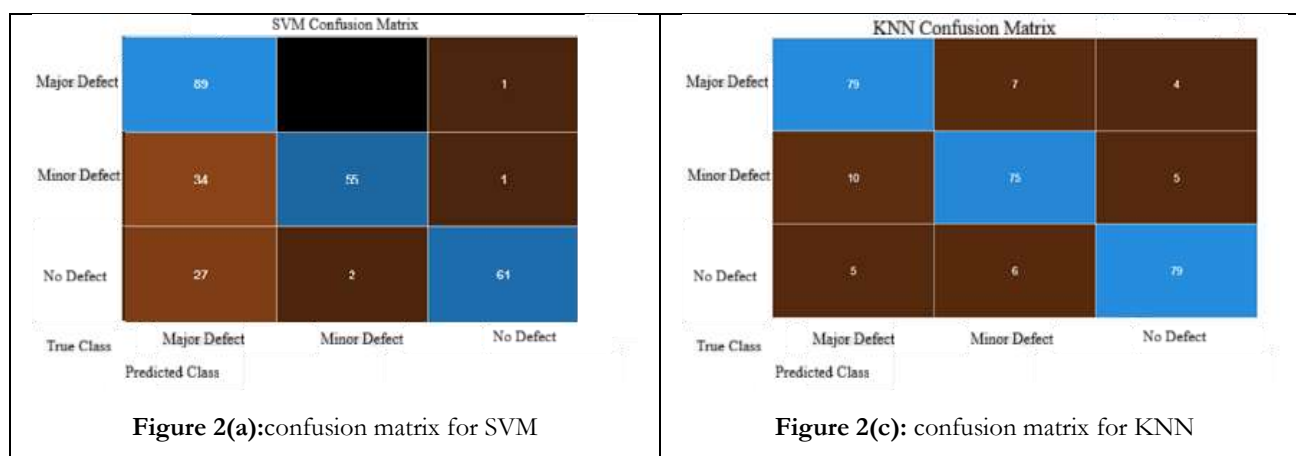
Table 4: Comparison of Models for different categories of images

Model	No defect				Minor defect				Major defect			
	A	P	R	F1	A	P	R	F1	A	P	R	F1
SVM	68	68	97	68	61	61	96	61	99	99	59	99
KNN	88	88	90	88	83	83	85	83	88	88	84	88
Random Forest	91	96	91	93	93	93	88	93	93	91	91	91
CNN		93	93	93		92	90	92		95	97	95

Table 5: Overall Model summary

Model	Average Accuracy (%)	Average F1 score (%)	Interface Time (S)
SVM	75.93	76.25	0.000016
KNN	86.30	86.30	0.000009
Random Forest	91.85	91.88	0.000072
CNN	93.33	93.33	0.012144

The confusion matrix of each of the technique is shown through figure 2(a), 2(b), 2(c) and 2(d) respectively for SVM, KNN, random forest and CNN.



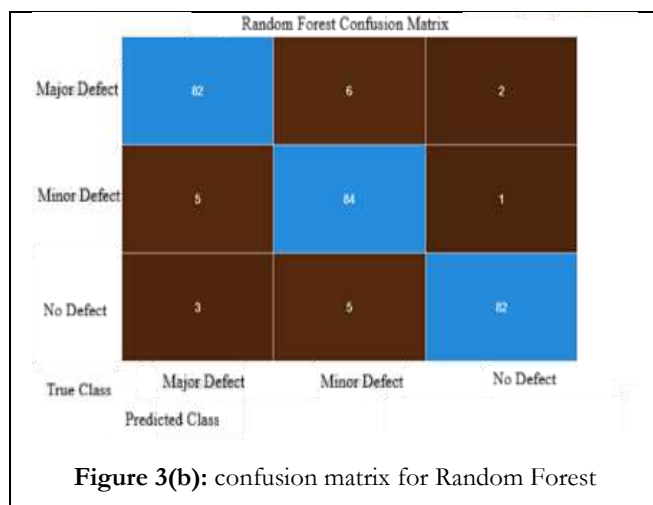


Figure 3(b): confusion matrix for Random Forest

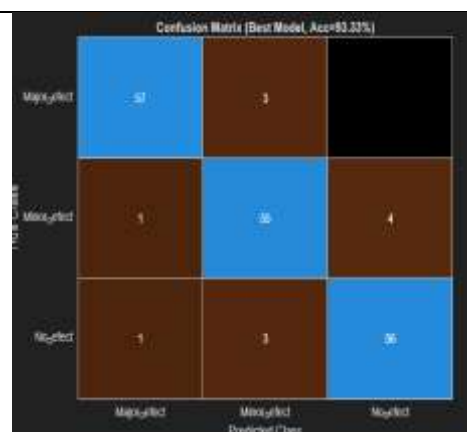


Figure 2(d): confusion matrix for CNN

The Random Forest appears to be robust to noisy, unbalanced or complex datasets of thermal images due to its ensemble nature that reduces over fitting by using predictions from multiple decision trees. It handles high-dimensional input well and requires less pre-processing. SVM on the other hand can achieve very high accuracy in classification tasks when the data classes are well-separated with clear decision boundaries of no defect and major defect. For thermal images dataset, the CNN achieves highest classification accuracy. CNN outperforms both Random Forest and SVM in fruit defect detection accuracy and feature learning but at the cost of higher data and computational demands. Random Forest is a robust, efficient alternative with very good accuracy and ease of use, while SVM is effective in specific cases but less scalable for complex image data. The sample results of image processing and defect class prediction with CNN model are shown in figure 3.

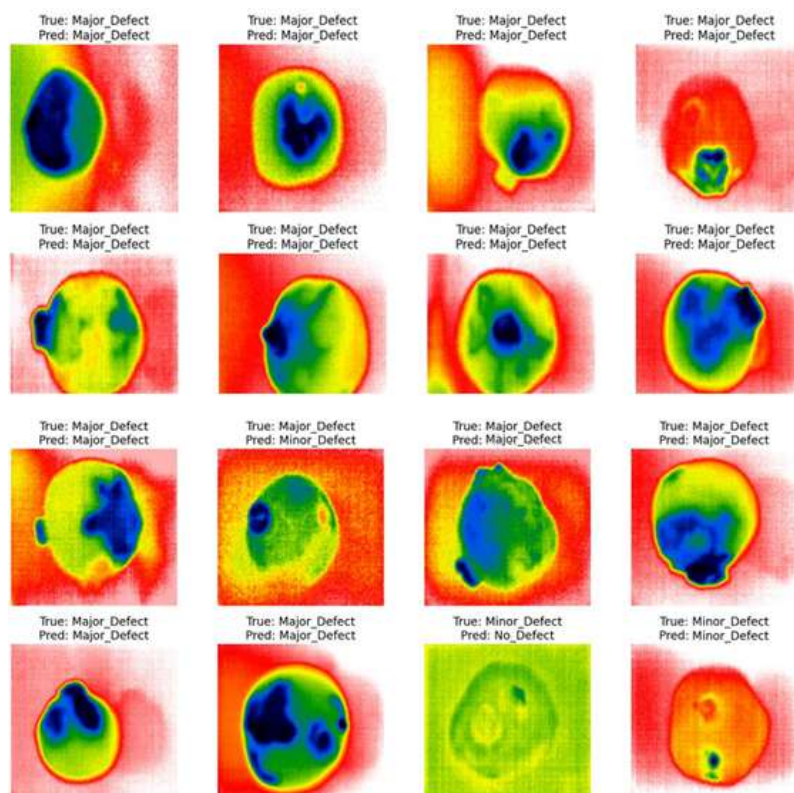


Figure 3: classification of thermal image of pomegranate in defect categories with CNN

4. CONCLUSION

The results of defect detection in pomegranate using thermal imaging, analyzed through SVM, KNN, Random Forest and CNN techniques, shows that deep learning models like CNN generally outperform traditional machine learning classifiers in accuracy and robustness, in complex thermal image patterns. The results show that CNN-based approaches can achieve high classification accuracy of 93.33% by automatically learning hierarchical features from thermal images, which makes them more effective at identifying internal defects or diseased regions at the expense of computation time. The SVM, KNN and Random Forest rely on feature extraction from thermal images and their performance is typically lower but still significant; SVM is effective when feature vectors are well-defined and high-quality, whereas Random Forest provides robustness against noise and variability in thermal data. The CNN techniques tend to deliver superior results due to their ability to capture intricate thermal patterns associated with different defect types, whereas SVM, KNN and Random Forest still offer reliable performance with less computational demand but are more sensitive to feature quality and selection.

ACKNOWLEDGEMENTS

Authors acknowledge department of computer engineering, A.C Patil College of Engineering, Kharghar, Navi Mumbai for their support for extending their facilities for creating this dataset

AUTHOR CONTRIBUTIONS

Ashvini Gaikwad: Conceptualization, Investigation.

Ashvini Gaikwad: Methodology, Laboratory Analysis.

Manoj Deshpande: Data Curation, Formal Analysis.

Varsha Bole: Supervision, Writing—Review & Editing.

CONFLICT OF INTEREST

Authors declare that they have no conflict of interest to influence the work presented in this paper.

ETHICS STATEMENT

The dataset used here made available in public. This data can be used with proper citation. No animals were involved and no food was wasted during this experimentation.

DATA AVAILABILITY

- [Pomegranate Thermal Images \(Original data\)](#) (Mendeley Data)

REFERENCES

- [1] Luca Mazzoni, Maria Teresa Ariza Fernández and Franco Capocasa, “Potential Health Benefits of Fruits and Vegetables”, MDPI Journal of Applied Science, Vol. 11, issue 19, 2021, <https://doi.org/10.3390/app11198951>
- [2] Rupali Santosh Kale, & Sanjay Shitole, “Non-destructive fruit quality assessment: a review on emerging trends in thermal imaging technology”, Journal of Computational Analysis and Applications (JoCAAA), Vol. 33, no. 08, 2024, pp. 326–341.
- [3] Jintao Feng, Qinyi Yang, Hao Tian, Zhipeng Wang, Shijie Tian, Huirong Xu, “Promising real-time fruit and vegetable quality detection technologies applicable to manipulator picking process”, International Journal of Agricultural and Biological Engineering, Vo. 17, No. 2, 2024, pp. 14–26
- [4] Ding C Q, Feng Z, Wang D C, Cui D, Li W H., “Acoustic vibration technology: Toward a promising fruit quality detection method”, Food Science and Food Safety, 2021; Vol. 20, No. 2, pp. 1655–1680, 10.25165/j.ijabe.20241702.7678
- [5] A. Prabhu, K. V. Sangeetha, S. Likhitha and S. Shree Lakshmi, "Applications of Computer Vision for Defect Detection in Fruits: A Review," 2021 International Conference on Intelligent Technologies (CONIT), Hubli, India, 2021, pp. 1-10, doi: 10.1109/CONIT51480.2021.9498393.

- [6] AnamZahraa, Rizwan Qureshib, Muhammad Sajjad, Ferhat Sadakd, Mehmood Nawazf, Haris Ahmad Khang, Muhammad Uzair, "Current advances in imaging spectroscopy and its state-of-the-art applications", *Expert Systems With Applications*, Vol. 238, article no. 122172, 2023
- [7] P. G, A. M, A. A, R. S and V. D, "Fruit Quality Detection Using Machine Vision Techniques," 2024 International Conference on IoT, Communication and Automation Technology (ICICAT), Gorakhpur, India, 2024, pp. 187-191, doi: 10.1109/ICICAT62666.2024.10923448.
- [8] Guina Wang, Zhen Li, Guirong Weng, Yiyang Chen, "An overview of industrial image segmentation using deep learning models", *Intelligence & Robotics*, Vol. 5, No. 1, 2025, pp. 143 – 180, 10.20517/ir.2025.09
- [9] Y. Ji, Q. Zhao, S. Bi and T. Shen, "Apple Grading Method Based on Features of Color and Defect," 2018 37th Chinese Control Conference (CCC), Wuhan, China, 2018, pp. 5364-5368, doi: 10.23919/ChiCC.2018.8483825.
- [10] L. Chaudhary and Y. Yogesh, "A Comparative Study of Fruit Defect Segmentation Techniques," 2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), Ghaziabad, India, 2019, pp. 1-4, doi: 10.1109/ICICT46931.2019.8977692.
- [11] A. L. Siridhara, K. V. Manikanta, D. Yadav, P. Varun and J. Saragada, "Defect Detection in Fruits and Vegetables using K Means Segmentation and Otsu's Thresholding," 2023 International Conference on Networking and Communications (ICNWC), Chennai, India, 2023, pp. 1-5, doi: 10.1109/ICNWC57852.2023.10127559.
- [12] Imran Hosen, Tahsina Tabassum, Jesmin Akhter, Imdadul Islam, "Detection of Fruits Defects Using Colour Segmentation Technique", *International Journal of Computer Science and Information Security (IJCSIS)*, Vol. 16, No. 6, June 2018, pp. 215 - 223
- [13] Yogesh, Ashwani Kumar Dubey, Rajeev Ratan Arora, Ashish Mathur, "Fruit Defect Prediction Model (FDPM) based on Three-Level Validation", *Journal of Non-destructive Evaluation*, 2021, pp. 40- 45
- [14] H. Patel, R. Prajapati and M. Patel, "Detection of Quality in Orange Fruit Image using SVM Classifier," 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2019, pp. 74-78, doi: 10.1109/ICOEI.2019.8862758.
- [15] P. A. Dharma Kenzhie, G. A. Kharisma, H. Lucky and Meiliana, "An Enhanced Approach for Defect Detection: Implementing CNN Algorithm and Identifying Catastrophic Forgetting," 2024 International Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM), Surabaya, Indonesia, 2024, pp. 1-6, doi: 10.1109/CENIM64038.2024.10882821.
- [16] K. K. Villanueva, J. A. M. Galindo, A. J. R. Tamayo, J. E. C. Rosal and D. I. E. Hisola, "Development of a Computer Vision Application for Mango (*Mangifera Indica* L.) Fruit Defect Detection Using YOLOv8 Architecture," 2024 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAET), Kota Kinabalu, Malaysia, 2024, pp. 483-487, doi: 10.1109/IICAET62352.2024.10730444.
- [17] S. Chakraborty, T. Alotwala, S. Arekar, D. Agrahari and H. Deshpande, "Lightweight Models for Fruit & Vegetable Defect Detection and Edge Deployment," 2025 5th International Conference on Soft Computing for Security Applications (ICSCSA), Salem, India, 2025, pp. 1016-1023, doi: 10.1109/ICSCSA66339.2025.11170816.
- [18] Naveen Kumar Mahanti, R. Pandiselvam, Anjineyulu Kothakota, Padma Ishwarya S., Subir Kumar Chakraborty, Manoj Kumar, Daniel Cozzolino, "Emerging non-destructive imaging techniques for fruit damage detection: Image processing and analysis", *Trends in Food Science & Technology*, Volume 120, February 2022, Pages 418-438, <https://doi.org/10.1016/j.tifs.2021.12.021>
- [19] Ashvini Gaikwad, Manoj Deshpande, Varsha Bhole, "Fruits Defect Detection: A Review with Image Processing Techniques", *Responsible Production and Consumption—Agricultural Sustainability and Food Security*, 2024, pp. 221 – 228 DOI: 10.1201/9781003542506-29
- [20] D. Jawale and M. Deshmukh, "Real time automatic bruise detection in (Apple) fruits using thermal camera," 2017 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2017, pp. 1080-1085, doi: 10.1109/ICCSP.2017.8286542.
- [21] Anjali N., Rajkumar Kannan, Frederic Andres and Georgeghita Ghinea, "Trend Review Related To Defects Detection from Fruits and Vegetables", *Preprints* 2021, 2021110035. <https://doi.org/10.20944/preprints202111.0035.v1>
- [22] Shrestha Ranjit and Wontae Kim, "Research on Defects Detection by Image Processing of Thermographic Images", *International Journal of Engineering and Technology (IJET)*, Vol 7 No 5, pp. 1849 – 1855, 2015.

- [23] N. Bui Ngoc Han, J. -H. Lee, D. Thanh Vu, I. Murtza, H. -G. Kim and J. -Y. Kim, "HAFREE: A Heatmap-Based Anchor-Free Detector for Apple Defect Detection," in IEEE Access, vol. 12, pp. 182799-182813, 2024, doi: 10.1109/ACCESS.2024.3504399.
- [24] C. Zhou, H. Wang, Y. Liu, X. Ni and Y. Liu, "Green Plums Surface Defect Detection Based on Deep Learning Methods," in IEEE Access, vol. 10, pp. 100397-100407, 2022, doi: 10.1109/ACCESS.2022.3206864
- [25] H. B. Patel and N. J. Patil, "Enhanced CNN for Fruit Disease Detection and Grading Classification Using SSDAE-SVM for Postharvest Fruits," in IEEE Sensors Journal, vol. 24, no. 5, pp. 6719-6732, 1 March1, 2024, doi: 10.1109/JSEN.2023.3342833.
- [26] A. Ren et al., "Machine Learning Driven Approach Towards the Quality Assessment of Fresh Fruits Using Non-Invasive Sensing," in IEEE Sensors Journal, vol. 20, no. 4, pp. 2075-2083, 15 Feb.15, 2020, doi: 10.1109/JSEN.2019.2949528.
- [27] Haiping Si, Yunpeng Wang, Wenrui Zhao, Ming Wang, Jiazhen Song, Li Wan, Zhengdao Song, Yujie Li, Bacao Fernando and Changxia Sun, "Apple Surface Defect Detection Method Based on Weight Comparison Transfer Learning with MobileNetV3", MDPI Journal of agriculture, Vol. 13, Article no. 824, 2023
- [28] Sara Vignati, Alessio Tugnolo, Valentina Giovenzana, Alessia Pampuri, Andrea Casson, Riccardo Guidetti and Roberto Beghi, "Hyperspectral Imaging for Fresh-Cut Fruit and Vegetable Quality Assessment: Basic Concepts and Applications", MDPI Journal of Applied Science, Vol. 13, Article no. 9740, 2023
- [29] Shilpa Gaikwad and Sonali Tidke, "Multi-Spectral Imaging for Fruits and Vegetables", International Journal of Advanced Computer Science and Applications, Vol. 13, No. 2, 2022
- [30] Kuo-Dung Chiou, Yen-Xue Chen, Po-Sung Chen, Ying-Tzy Jou, Shang-HanTsai & Chia-Ying Chang, "Application of deep learning for fruit defect recognition in Psidium guajava L", Scientific Reports, Vol. 15, Article no. 6145, 2025, <https://doi.org/10.1038/s41598-025-88936-y>
- [31] Ashvini Gaikwad, Manoj Deshpande, Varsha Bhole, "Dataset creation of thermal images of pomegranate for internal defect detection", Data in brief, Volume 60, June 2025, 111538, doi: <https://doi.org/10.1016/j.dib.2025.111538>
- [32] R. S. Kale and S. Shitole, "Thermal Imaging Based Quality Assessment of Pomegranate," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10307853.