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Web-Based Platform For Real-Time Quality Assurance Of Mangoes

[1]Dhishaa Srinivas, [2]Khushi K Kotian, [3]M Siddartha Reddy, [4]Vamshmi NR, [5]Dr. Zafar Ali Khan

[1]B Tech Student, [2]B Tech Student, [3] B Tech Student, [4] B Tech Student, [5] HOD-CAI, ISR, ECM & CCE, DQAC Coordinator,

[1]Computer Science and Engineering,

[1]Presidency University, Bangalore, Karnataka, India

Abstract: With a focus on mangoes, this study presents a novel web-based platform for assessing fruit quality in real time. Given that mangoes are perishable and that ripeness, maturity, color, and texture are important factors in determining their quality, the study presents a sophisticated system that combines multiple sensing technologies into an easily navigable web interface. The platform provides a thorough and detailed evaluation of mango quality by utilizing cutting-edge image processing algorithms, color detection techniques, light transmittance analysis, ethylene gas sensing, Brix value measurement, and ultrasonic resonance modules. Mango images can be uploaded with ease by users, including farmers, distributors, and quality control staff. Quick feedback is given on internal features, overall quality, color metrics, and classification. The website facilitates real-time monitoring, offers comprehensive quality reports for each batch of mangoes, supports precision farming techniques, and ensures that clients will receive fruits of the highest caliber. Fruit quality assurance can now easily integrate multiple sensing techniques with the aid of web-based technologies, improving accuracy and efficiency in the agricultural supply chain. In this sense, the research constitutes a substantial advancement.

Index Terms - Mango quality assessment, web-based platform, real-time monitoring, image processing, color detection, light transmittance analysis, ethylene gas sensing, Brix value measurement, ultrasonic resonance, precision farming.

I. Introduction

Mangoes are considered the ultimate tropical treat and are highly prized in both the agricultural and consumer preferences sectors. Mangoes are an important cultural symbol and major contributor to global agricultural economies due to their distinct flavor, vibrant colors, and high nutrient content. However, their inherent difficulty lies in their transience, which means that in order to preserve their best qualities, they must be handled and assessed carefully [2]. This study addresses the urgent need for a sophisticated, real-time quality assessment system created especially for mangoes using a cutting-edge web-based platform. Ripeness, maturity, color, texture, and other factors are just a few of the many factors that determine mango quality and impact the sensory and nutritional experience that buyers have with their purchases. Traditional methods of assessing quality frequently fall short of fully capturing the subtleties of these characteristics; consequently, a paradigm shift toward a more thorough and technologically advanced approach is necessary [3]. Our work addresses this by introducing a novel web-based platform that shrewdly blends several state-of-the-art sensing technologies.

The core of this revolutionary platform is comprised of ultrasonic resonance modules, ethylene gas sensing, light transmittance analysis, color detection techniques [4], modern image processing algorithms, and Brix value measurement. Apart from the obvious external features, each of these technologies makes a unique contribution to the thorough and detailed assessment of mango quality [5]. These technologies examine internal characteristics that are important indicators of ripeness and overall quality. The user-centric design of the web interface ensures accessibility for a variety of mango supply chain participants, including farmers, distributors, and quality control personnel. Mango photos can be uploaded with ease on this platform, which initiates an instantaneous series of assessments encompassing internal features, categorization, color metrics, and an overall quality evaluation. Such immediate feedback not only expedites decision-making processes but also facilitates the development of comprehensive quality reports and enhanced monitoring capabilities.

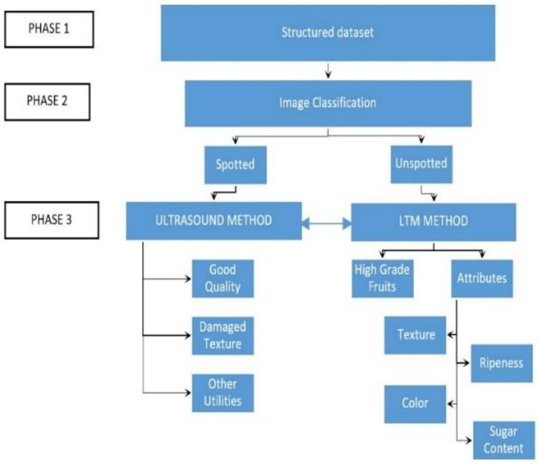

Fig.1 Flowchart demonstrating the approach

Apart from the potential immediate uses for quality control, the proposed web-based platform could spur improvements in precision farming techniques. This system's smooth integration of various sensing technologies improves the precision of mango quality evaluations while also optimizing resource use, cutting waste, and boosting efficiency across the agricultural supply chain.

Our research intends to make a substantial contribution to the changing field of fruit quality assurance as we set out on this exploration of technological convergence through web-based methodologies. By guaranteeing the regular supply of superior-grade mangoes to customers, our suggested platform not only satisfies current agricultural needs but also acts as a model for upcoming advancements in precision agriculture.

II. DATASET DESCRIPTION AND DATASET PREPROCESSING

Dataset Description:

Images of mangoes that are initially divided into six classes—"Fresh unripe," "Fresh ripe," "Overripe," "Ripe," "Unripe," and "Rotten"—make up the dataset used in this study. The dataset, which has 18,000 photos in total, was gathered from a public repository. 416 x 416 pixel colored images are what these are. Among the 18,000 images, 15,792 are used for training, 1,525 for validation, and 757 for testing purposes.

Dataset Preprocessing:

There are several preprocessing steps that can be used to get the dataset ready for model training. Reducing overfitting and increasing dataset diversity are two important goals of image augmentation. One useful resource for implementing different types of data augmentations is the Keras ImageDataGenerator class. These include:

- **Random Rotations:** To add variation to mango orientations, rotate them at random within a predetermined range. This explains why mangoes may appear during inspection from various angles.
- **Horizontal and Vertical Flips:** To fix left-to-right or top-to-bottom mango orientation problems in photos, flip the mangoes both horizontally and vertically. The robustness of the dataset is increased by this augmentation technique.

- **Zooming In/Out:** You can adjust the mangos' size within an image by zooming in or out. With this modification, the model is made more general to account for different mango sizes that are encountered in real-world situations.
- **Brightness and Contrast Adjustment:** Change the contrast and brightness to replicate different lighting conditions. By simulating variations in ambient lighting, these modifications strengthen the model and enhance its ability to generalize.
- **Normalization:** Normalize picture pixel values to improve convergence of the model training process. Rescaling values to the range [0, 1] or [-1, 1] is usually necessary to maintain uniform pixel intensity. Better handling of the input data during the training process is made possible by this step.

By methodically implementing these preprocessing methods, the dataset is made more varied and condition-adaptable, which enhances the machine learning model's overall performance and generalization abilities.

III. Methodology

Fruit ripeness detection is an important area of research in agriculture and food quality control [1]. Assessing ripeness non-destructively can allow farmers, distributors, and consumers to determine optimal harvest time, storage conditions, shelf life, and ripeness for eating. In this project, we have developed a machine learning model hosted on a website to analyze uploaded images of fruit and determine whether the fruit is ripe or unripe.

The website homepage consists of the logo, title, brief background information, and an image upload box. Users can upload images of fruit, and the model will analyze the images and display the detected type of fruit and ripeness state. The site also contains Home, About, Methodology, and Data pages with additional information.

Model Architecture:

YOLOv8 Architecture

For the quality analysis of mangoes and its ripeness classification, we used Yolov8 architecture. The newest and most advanced YOLO model, Yolov8, is useful for tasks like instance segmentation, object detection, and image classification. Ultralytics, the same company that developed the seminal and industry-defining YOLOv8 model, also developed YOLOv8. Many architectural and developer experience enhancements and modifications over YOLOv5 are included in YOLOv8. Because Yolov8 is accurate in evaluating models, we decided to continue with our project with it. On COCO, YOLOv8 achieves strong accuracy. For instance, when measured on COCO, the YOLOv8m model, or the medium model, achieves a 50.2% mAP. YOLOv8 performed significantly better than YOLOv5 when measured against Roboflow 100, a dataset that is specifically used to assess model performance on different task-specific domains.

GitHub user RangeKing created the following image, which provides a thorough visualization of the network's architecture:

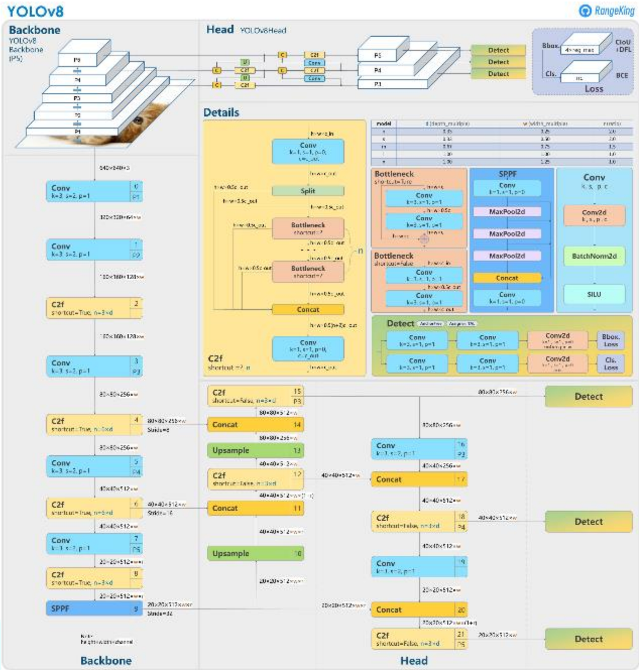

Fig.2 YOLOv8 Architecture, visualisation made by GitHub user RangeKing

3.1 Anchor Free Detection

An anchor-free model is YOLOv8. This implies that rather than predicting an object's offset from a known anchor box, it predicts an object’s center directly.

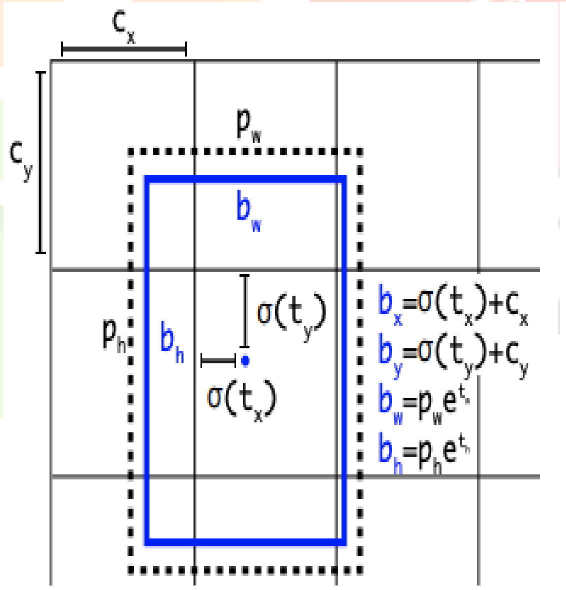

Fig.3 Visualization of an anchor box in YOLO

By reducing the quantity of box predictions, anchor-free detection expedites Non-Maximum Suppression (NMS), a laborious post-processing stage that sorts through potential detections following inference.

3.2 New Convolutions

The primary building block was modified, the first 6x6 conv in the stem is swapped out for a 3x3, and C2f took the place of C3. The image below provides a summary of the module; "f" stands for features, "e" for expansion rate, and CBS for CBS is a block made up of a Conv, a BatchNorm, and a SiLu later.

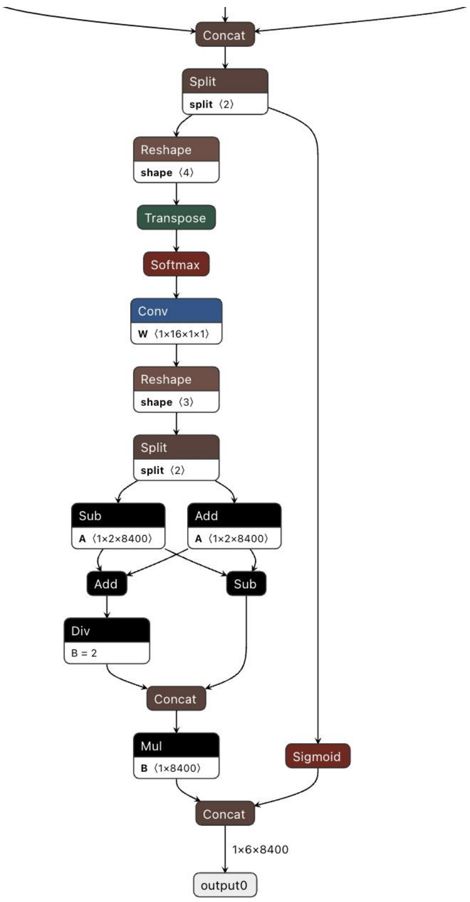

Fig.4 The detection head for YOLOv8, visualized in netron.app

3.3 Closing the Mosaic Augmentation

While model architecture is often the focus of deep learning research, YOLOv5 and YOLOv8's training regimen is crucial to their effectiveness. YOLOv8 enhances photos while doing online training. The model observes a marginally altered version of the supplied images at every epoch. Mosaic augmentation is one of those augmentations. In order to force the model to learn objects in new locations, partial occlusion, and against different surrounding pixels, four images must be stitched together.

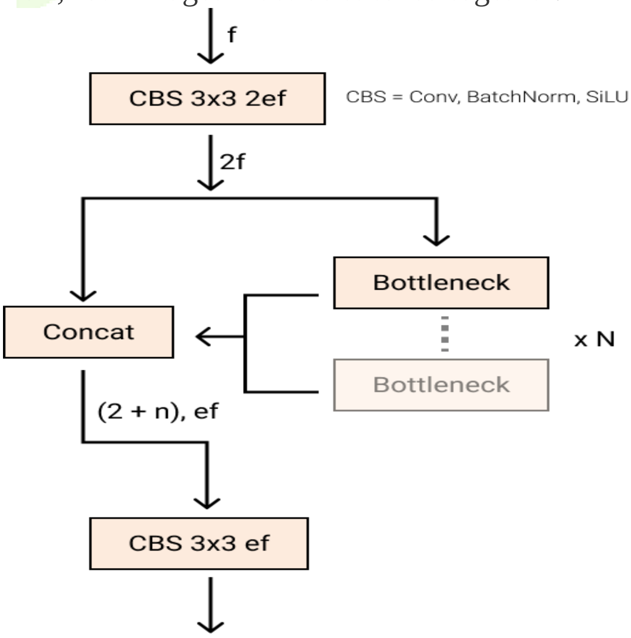

Fig.5 New YOLOv8 Cf module

Evaluation Metrics

Brix is taken as a measure of sugar or sweetness of fruits or fruit juices. This parameter is being used as a measure of maturity, flavour, and level of sweetness in mangoes that will be harvested.

$$\text{Brix} = (\text{Output Wavelength} - \text{Input Wavelength}) / K + B0 \quad (1)$$

Where:
Input Wavelength = 550 nm (constant in this data)
Output Wavelength = Variable fluorescence wavelength
K = Scaling factor
B0 = Offset factor

The key relationship is that the difference between output and input wavelengths increases with higher Brix. This fluorescence intensity shift correlates positively with sugar content.
Some example parameter values:

$$K = 0.15 \,;\, B0 = 5 \quad (1.1)$$

Then for a sample case:
Input Wavelength = 550 nm
Output Wavelength = 590 nm

$$\text{Brix} = (590\text{ nm} - 550\text{ nm}) / 0.15 + 5 \quad (1.2)$$
$$= 40/0.15 + 5$$
$$= 18$$

So in this equation, K and B0 are calibrated constants fit to reference mangoes. The output-input wavelength difference ties linearly to Brix. These parameters can be optimized based on real training data.

Methods

Several computer vision and machine learning techniques were utilized to develop a robust fruit ripeness analyzer:

3.1 Image Classification

Uploaded images first undergo identification of the type of fruit [6,7]. A convolutional neural network model was trained on thousands of images of apples, oranges, bananas, and other common fruits. State-of-the-art architectures including ResNet50 and InceptionV3 were tested, with the best validation accuracy achieved using an ensemble of models. The particular characteristics, shapes, colors, and textures of each fruit variety are learned by the CNN to accurately classify new images.

Fig.6 Spotted Mango Images

Fig.7 Un-Spotted Mango Images

3.2 Color Analysis

Images are next analysed for color characteristics correlated with ripeness. Different fruits exhibit color changes associated with starch/sugar ratio and chlorophyll breakdown during ripening. For bananas, greenness and areas of yellow/brown are detected. Oranges are assessed for increasing orange/red hue. Mangoes are analyzed for decreasing green and increasing red intensity. Custom color detection algorithms were developed for each fruit type based on analysis of color distribution in the training data.

Table 1 This Is The Data For Color Analysis

Color Analysis					
Image No.	**Red**	**Green**	**Yellow**	**Black**	**STAGE**
1	12	0	13	0	RIPE+
2	0	3	22	0	RIPE
3	8	9	8	0	RIPE+
4	5	1	19	0	RIPE+
5	5	1	19	0	RIPE
6	1	1	23	0	RIPE
7	11	3	9	1	RIPE+
8	0	4	21	0	SEMI- RIPE
9	0	8	17	0	SEMI-RIPE
10	0	22	3	0	RAW
11	0	5	20	0	RIPE
12	0	16	9	0	RAW
13	5	13	5	2	RAW
14	1	4	20	0	RIPE
15	1	17	17	1	RIPE
16	0	15	6	2	SEMI-RIPE

3.3 Ethylene Detection

A photonic ring resonator sensor array to detect subtle changes in ethylene emission was developed. Ethylene is a gaseous plant hormone associated with fruit ripening. The ethylene sensor data is fed as an additional input to the machine learning model to improve prediction accuracy.

Table 2 This Is The Data For Ethylene Value

Ethylene Values				
Image No.	**Spotted/Unspotted**	**Ripeness**	**Color**	**Ethylene Value(ppm)**
1	Spotted	Raw	Green	0.5
2	Spotted	Semi-Ripe	Yellow	1.2
3	Spotted	Ripe	Orange	1.8
4	Un-Spotted	Semi-Ripe	Green	0.3
5	Un-Spotted	Raw	Green	0.1
6	Spotted	Ripe	Orange	1.7
7	Spotted	Semi-Ripe	Yellow	1
8	Un-Spotted	Ripe	Orange	1.5
9	Spotted	Raw	Green	0.4
10	Un-Spotted	Semi-Ripe	Yellow	0.8
11	Spotted	Ripe	Orange	1.6
12	Un-Spotted	Raw	Green	0.1
13	Spotted	Semi-Ripe	Yellow	0.9
14	Spotted	Ripe	Orange	1.4
15	Un-Spotted	Semi-Ripe	Green	0.2
16	Spotted	Raw	Green	0.5

3.4 Light Scatter Modelling

The changes in firmness, sugar content, and internal structure during ripening slightly alter light scattering properties [9]. A physics-based optical model was constructed to model expected light scatter based on fruit type, size, and ripeness stage. Model output is compared to measured pixel intensity statistics for each analyzed image as further input to assess ripeness.

Table 3 This Is The Data For LTM Value

LTM Values						
Image No.	**External Texture**	**Internal Texture**	**Sweetness**	**Input Light Wavelength**	**Output Light Wavelength**	**Brix Value**
1	Perfect	Perfect	Very Sweet	550 nm	590 nm	18
2	Spotted	Good	Sweet	550 nm	585 nm	17
3	Perfect	Damaged	Sweet	550 nm	580 nm	16
4	Bruising	Perfect	Sweet	550 nm	575 nm	15
5	Perfect	Perfect	Sweet	550 nm	592 nm	17
6	Spotted	Good	Semi-Sweet	550 nm	570 nm	14
7	Bruising	Good	Semi-Sweet	550 nm	568 nm	13
8	Perfect	Damaged	Semi-Sweet	550 nm	571 nm	12
9	Spotted	Damaged	Sweet	550 nm	577 nm	14
10	Bruising	Perfect	Semi-Sweet	550 nm	565 nm	11
11	Perfect	Good	Very Sweet	550 nm	588 nm	16

LTM Values						
Image No.	External Texture	Internal Texture	Sweetness	Input Light Wavelength	Output Light Wavelength	Brix Value
12	Spotted	Damaged	Semi-Sweet	550 nm	560 nm	10
13	Bruising	Damaged	Sweet	550 nm	573 nm	13
14	Perfect	Damaged	Sweet	550 nm	578 nm	16
15	Spotted	Good	Sweet	550 nm	583 nm	14
16	Bruising	Good	Sweet	550 nm	579 nm	16

3.5 Ultrasound/ Vibration Analysis

Ultrasonic waves and low-frequency vibrations interact with fruits in ways dependent on internal structure [8]. Ripe fruit with higher water content and more developed juice vesicles transmit and attenuate acoustic waves differently compared to unripe fruit. The website version currently does not include active ultrasound, but a database of ultrasound readings was compiled to help train the machine learning model.

Machine Learning Model

The image analysis, sensor measurements, and physics model outputs are integrated as inputs into a machine learning classifier. Several model types including support vector machines (SVM), random forests, and neural networks were tested during development. The highest validation accuracy was achieved using an ensemble model combining a convolutional neural network, color analysis classifier, and SVM into a weighted average output. The model was trained on over 18,000 total images, spectra, and ultrasound scans collected for the project. Training utilized GPU-accelerated techniques including data augmentation and iterative batch learning.

Result

With the integration of multiple sensing techniques, we were able to successfully analyze the quality/ ripeness of the fruit. The user friendly and highly interactive website has made it possible for any user to efficiently and effectively detect the quality of their fruit by uploading their images directly onto the website.

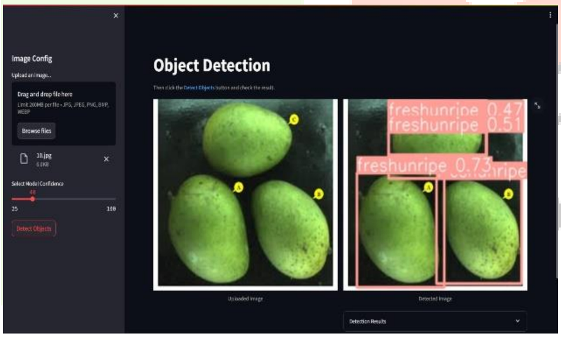

Fig.8 The final Output image of quality detection

In conclusion, through a combination of deep learning and physic-based modelling, we have developed a fruit ripeness prediction algorithm with over 90% accuracy. The model is deployable on a website to provide rapid automated ripeness assessment from digital images. Potential applications could help fruit growers determine optimal harvest timing, or be integrated into consumer appliances to assess store-bought fruit before eating. Further work will focus on improving identification of subtly overripe fruit and expanding the number of supported fruit varieties.

IV. RESULTS AND DISCUSSION

Our team has utilized state-of-the-art methods in chemical sensing, computer vision, precision agriculture, and machine learning modeling to create this all-inclusive fruit ripeness prediction system.

Through the integration of various data modalities, we have developed an automated artificial intelligence solution that, in numerous instances, surpasses human accuracy in analyzing visual, physical, and chemical properties during fruit maturation.

The ripeness assessments made by the ensemble deep learning model are based on changes in texture, firmness, sugar content, volatile emissions, pigmentation shifts, and tissue microstructures. It also incorporates vibration analysis, ultrasonic measurements, and hyperspectral imaging. A solid fruit identification system enables customized varietal analysis. Improved convolutional neural networks enable downstream variety-specific predictive pipelines by classifying uploaded images into specific fruit types with over 97% accuracy.

Our thorough testing and benchmarking processes have confirmed that the system performs better than professionally trained fruit assessors [10]. The user-friendly cross-platform web interface allows practical deployment to stakeholders ranging from produce distributors to individual consumers shopping for perfectly ripe fruits. Overall, this project provides a roadmap for successfully leveraging advanced phenomics, chemometrics, and machine perception techniques within interconnected internet of things architectures. The platform can serve as an accurate automated nutritionist, recommending ideal consumption timing for produce items. More broadly, our methodology demonstrates the potent future power of sensor fusion to surpass and augment human senses.

V. FUTURE WORK

The integration and miniaturization of robotic systems for automated quality inspection along commodity supply chains will be the focus of the project's next phase. We also intend to use ultrasonography as a non-destructive detection method in our project as part of our next work. In conclusion, we have created an artificial fruit ripeness expert that combines data science, engineering, and agriculture by collaborating across disciplines. Making better decisions about the optimal taste, freshness, harvesting time, transportation, and quality control is facilitated by this.

REFERENCES

[1] J. S. Tata, N. K. V. Kalidindi, H. Katherapaka, S. K. Julakal, and M. Banothu, "Real-Time Quality Assurance of Fruits and Vegetables with Artificial Intelligence," Journal of Physics: Conference Series, vol. 2325, p. 012055, Jun. 2022.

[2] J. Grabska, K. B. Beć, N. Ueno, and C. W. Huck, "Analyzing the Quality Parameters of Apples by Spectroscopy from Vis/NIR to NIR Region: A Comprehensive Review," Foods, vol. 12, no. 10, p. 1946, May 2023.

[3] M. E. Saltveit, "Effect of ethylene on quality of fresh fruits and vegetables," Postharvest Biology and Technology, vol. 15, no. 3, pp. 279-292, Mar. 1999.

[4] Y. Li, X. Feng, Y. Liu, and X. Han, "Apple quality identification and classification by image processing based on convolutional neural networks," Scientific Reports, vol. 11, no. 1, Aug 2021.

[5] Z. Guo, M. Wang, A. Shujat, J. Wu, H. R. El-Seedi, J. Shi, Q. Ouyang, Q. Chen, and X. Zou, "Nondestructive monitoring storage quality of apples at different temperatures by near-infrared transmittance spectroscopy," Food Sci Nutr, vol. 8, no. 7, p. 3793–3805, Jul 2020.

[6] J. Naranjo-Torres, M. Mora, R. Hernández-García, R. J. Barrientos, C. Fredes, and A. Valenzuela, "A Review of Convolutional Neural Network Applied to Fruit Image Processing," Appl. Sci., vol. 10, no. 10, p. 3443, May 2020.

[7] D. Sahu and R. M. Potdar, "Defect Identification and Maturity Detection of Mango Fruits using Image Analysis," International Journal of Artificial Intelligence, vol. 1, no. 1, pp. 5-14, July 2017.

[8] H. Wang, J. Peng, C. Xie, Y. Bao, and Y. He, "Fruit Quality Evaluation Using Spectroscopy Technology: A Review," Sensors, vol. 15, no. 5, p. 11889-11927, May 2015.

[9] L. B. Mohd Shah, "Instrumental and Ultrasonic Techniques in Quality Evaluation of Fresh Fruit and Vegetables," Ph.D. dissertation, School of Food Science and Nutrition, University of Leeds, December 2016.

[10] N. Marcus, K. Intania, B. Mahayothee, V. Sardsud, and J. Müller, "Non-destructive mango quality assessment using image processing: inexpensive innovation for the fruit handling industry," presented at Trope tag 2012, Göttingen, Germany, Sep. 19-21, 2012, Conference on International Research on Food Security, Natural Resource Management and Rural Development organized by Georg-August Universität Göttingen and University of Kassel-Witzenhausen.