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COMPARATIVE ANALYSIS OF AI AND DEEP LEARNING TECHNIQUES FOR DETECTING CHEMICALLY RIPENED FRUITS, CHALLENGES AND FUTURE DIRECTIONS

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Abstract:
Automatic detection of chemically ripened fruits has become an active area of research in recent years due to rising food safety concerns and awareness regarding fruit quality degradation and health hazards caused by the misuse of artificial ripening agents. Manual techniques for detecting fruit ripeness rely on visual cues or destructive sensing, which are inherently subjective and can hardly be scaled for agricultural purposes. Several attempts have been made to leverage Artificial Intelligence (AI) & Deep Learning for automatic and non-destructive detection of fruit ripeness. In this paper, we survey current state-of-the-art methodologies while comparing their strengths & weaknesses, majorly focusing on thermal image-based approaches for the detection of chemically ripened fruits. Existing machine learning approaches like SVMs & Random Forests are computationally less expensive and are preferred in low-resource settings, while Deep Learning models, especially CNNs, have proven to perform better in terms of classification accuracy since they have the ability to automatically extract features from input data. Hybrid approaches attempting to strike a balance between accuracy and resource constraints have also shown promise according to some studies. While surveying existing works, we found that a majority of works use visible spectrum imaging for detection, while the use of thermal images for this application has been relatively unexplored. Most works also do not focus on model interpretability/explainability or real-time deployment, which hinders their use in practical applications. According to our survey, thermal imaging can prove to be a potential non-destructive approach for this problem, and future works should aim at creating accurate, explainable AI frameworks that can be deployed in real time.

Keywords: Chemically Ripened Fruits, Thermal Imaging, Artificial Intelligence, Deep Learning, Convolutional Neural Networks (CNN), Non-Destructive Detection.

I. Introduction:

Ripening of fruits is a natural process involving complex changes that influence the texture, colour, flavour, and nutritional quality. In commercial agriculture, artificial ripening techniques are often used to accelerate this process to meet market demands. Chemicals like ethephon and calcium carbide are commonly applied to induce ripening. Their excessive or improper use can adversely affect fruit quality and pose potential health risks to consumers. Which leads to the identification of chemically ripened fruits has become an important challenge in ensuring food safety and quality control. Conventional methods used to detect fruit ripeness rely on visual inspection, manual evaluation, or lab tests. These approaches are often subjective, time taking hence not suitable for large scale or real-time applications [1]. In recent years, Artificial Intelligence (AI) and Deep Learning (DL) evolved so much that enables automation and non-destructive techniques for fruit classification and quality maintenance [2]. Most recent studies utilize RGB imaging or hyperspectral data however, these methods are either sensitive to environmental conditions or require expensive and complex equipment. While thermal imaging emerged as a promising alternative, since it captures temperature variations associated with internal physiological changes in the ripening process [3]. Unlike conventional imaging methods, thermal imaging is less affected by external lighting and provides a non-invasive means of analysing fruit characteristics. Despite its potential, the application of thermal imaging combined with AI techniques for detecting chemically ripened fruits remains relatively underexplored [4]. This paper aims to review existing AI and DL techniques for fruit ripeness detection, with a particular focus on thermal imaging-based approaches. Study shows the strengths, limitations, and real-time applicability of different methods. Also identify key research gap to help in development of efficient, non-destructive, and interpretable detection systems.

II. Existing Methodology:

A. **Traditional Machine Learning Method:** Traditional Machine learning methods first extract colour, texture, and shape from fruit images, which are then used as input. Here, two models are used: Support Vector Machine (SVM) and K-Nearest Neighbours (KNN). SVM defines the boundary between naturally and chemically ripened fruits, and by comparing the nearest neighbour, KNN gives similarity between naturally and chemically ripened fruits. Finally, these methods are combined to make a final decision. This method is entirely based on surface-level features, meaning it works on visible features. It cannot detect internal chemical changes in fruits, so it is very difficult to differentiate between naturally and chemically ripened fruits[7].

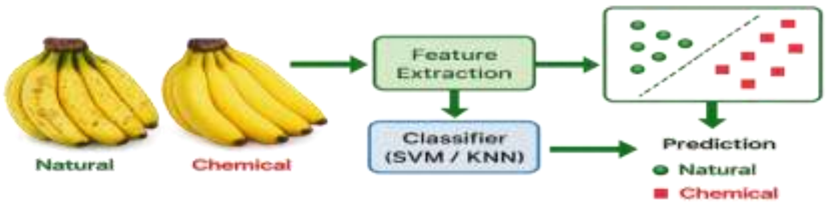

Fig.1 Traditional Machine Learning Method

Mathematical Representation:

1. SVM Decision Function: This is the standard SVM hyperplane equation used for binary classification.

$$f_{SVM}(x) = w^T x + b$$

Where:

$x \rightarrow$ Input feature vector (color, texture, shape of fruit)
$w \rightarrow$ Weight vector (defines orientation of decision boundary)
$w^T \rightarrow$ Transpose of weight vector
$b \rightarrow$ Bias (shifts the hyperplane)
$f_{SVM}(x) \rightarrow$ Decision value (used to classify the fruit)
Interpretation:
$f_{SVM}(x) > 0 \rightarrow$ Naturally ripened
$f_{SVM}(x) < 0 \rightarrow$ Chemically ripened

2. Uncertainty Condition:

The following equation is specifically designed for chemically ripened fruit detection. This helps to identify uncertain SVM predictions near the decision boundary. Leading to activate KNN refinement.

$$\text{Mode of } f_{SVM}(x) < \epsilon$$

Where:

$| f_{SVM}(x) | \rightarrow$ Distance from decision boundary
$\epsilon \rightarrow$ Threshold for uncertainty

3. KNN Distance Function: standard Euclidean distance equation for KNN classification.

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2}$$

Where:

$x_i \rightarrow$ Test sample (fruit to classify)
$x_j \rightarrow$ Training sample
$n \rightarrow$ Number of features
$x_{ik}, x_{jk} \rightarrow$ Feature values
$d(x_i, x_j) \rightarrow$ Distance between two samples
Interpretation: A smaller distance indicates greater similarity between fruits.

4. KNN Prediction: KNN predicts the class using majority voting among nearest neighbours.

$$Y_{KNN}$$

Where:

$Y_{KNN} \rightarrow$ Class predicted by KNN

5. SVM Prediction: The sign of the SVM decision function determines the final class label.

$$Y_{SVM}$$

Where:
Y_{SVM}→ Class predicted by SVM

6. Final Decision (Voting): The following equation is specifically designed for chemically ripened fruit detection. It combines outputs from both classifiers using majority voting.

$$Y = \text{mode}\ (Y_{SVM}, Y_{KNN})$$

Where:
Y→ Final predicted class
mode → most frequent output

7. Weighted Hybrid Score: Following equation combines SVM confidence and KNN similarity into a unified hybrid score for chemically ripened fruit.

$$Score = \alpha \cdot f_{SVM}(x) + \beta \cdot (1/d_{KNN})$$

Where:
α, β→ Weights (importance of each method)
$f_{SVM}(x)$→ SVM confidence
d_{KNN}→ Distance from neighbors
$1/d_{KNN}$→ Similarity score

B. Neural Networks Method:
Neural Networks are used for fruit ripeness detection as their ability to automatically learn features from data. Here, raw fruit images are directly given as input to the model without manual feature extraction. ANN are used to process input through multiple layers of neuron. CNN is specifically designed for image data which uses convolutional layers for extraction spatial features such as edges, textures, and patterns. The network learns hierarchical representations of fruit characteristics during training and classifies the fruit as naturally or chemically ripened. CNN models are particularly effective as they capture complex visual patterns that traditional methods fail to detect [8].

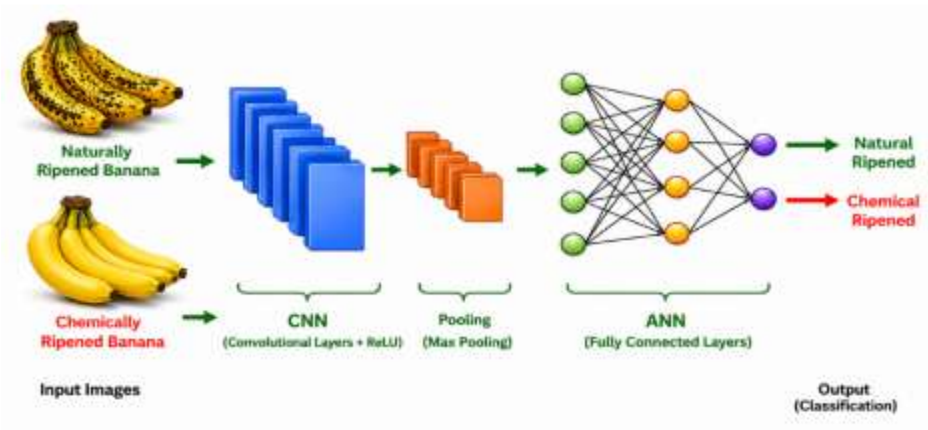

Fig 2. Neural Networks Method

Mathematical Representation:

Artificial Neural Network (ANN): The mathematical formulations used in this method are based on standard ANN and CNN equations commonly employed in deep learning and image classification. The output of a neuron is computed as a weighted sum of inputs followed by an activation function:

$$y = f(\sum_{i=1}^{n} w_i\, x_i + b)$$

Where:
x_i→ Input features (fruit image features)
w_i→ Weights
b→ Bias
$f(\cdot)$→ Activation function
y→ Output of neuron
Above formula represents how an artificial neuron processes fruit image features.

Convolutional Neural Network (CNN):

Below equation performs feature extraction from fruit images. CNN automatically identifies: surface texture, spots, edges, thermal variations, colour distribution. These features helps to distinguish naturally ripened fruits from chemically ripened fruits. Feature extraction in CNN is performed using convolution operation:

$$O_{i,j} = \sum_m \sum_n I_{i+m,j+n} \cdot K_{m,n}$$

Where:
I→ Input image
K→ Convolution kernel (filter)
$O_{i,j}$→ Output feature map

Activation Function (Non-linearity)
This is a predefined activation function commonly used in CNN and ANN models.

$$f(x) = max\ (0, x)$$

Output Probability (Classification Layer)
This equation converts output scores into probabilities for classification as Naturally Ripened and Chemically Ripened. The class with highest probability is selected as the final prediction. This is a standard probability distribution equation used in classification networks.

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

Loss Function (Model Optimization)
This equation measures the difference between actual fruit class labels, predicted fruit class labels. The model minimises this loss during training to improve classification accuracy.

$$L = -\sum y_i log\ (\hat{y}_i)$$

C. Sensor-Based Method:
The sensor-based method uses chemical and environmental measurements to distinguish naturally ripened fruits from chemically ripened fruits. This method does not analyse the external appearance of the fruit. It uses different sensors to collect values of the fruit and gives a final decision. It measures the value of ethylene concentration by using a gas sensor. A gas sensor is a sensor that measures the amount of gas released by the fruit. pH value is collected by using a pH sensor, where the pH sensor detects chemical changes during ripening. The temperature sensor and humidity sensor record the surrounding environmental temperature.
After collecting data, to improve the accuracy, the data is cleaned and normalised, and then processed sensor readings are given to the machine learning models. This model learns the pattern and classifies fruit as either naturally ripened or chemically ripened [9].

Fig. 3 Sensor-Based Method

Mathematical Validation:
The following equation was developed by the author to describe input features, including gas concentration, pH, and humidity, for fruit ripeness detection.

$$F_{sensor} = [G, pH, H]$$

Where:
G→ Gas concentration (ethylene)
pH→ Acidity level

$H \rightarrow$ Humidity
Feature Normalisation:
Standard Z-score normalisation formula used in Machine Learning, Data preprocessing, and Pattern recognition. It scales sensor readings into a common range.

$$F' = \frac{F - \mu}{\sigma}$$

Different sensors produce values in different ranges. Normalisation prevents one sensor from dominating the learning process.
Classification Function (Generic Model):
The mapping between sensor features and output classification is represented in following derivation. It means the machine learning model f takes sensor data as input, predicts whether the fruit is naturally or chemically ripened. It is a generalised functional representation commonly used in machine learning theory.

$$Y = f(F_{sensor})$$

Interpretation
Sensor values represent **internal chemical changes**
Normalisation ensures consistent scale
Model learns mapping between sensor data and ripening type
This method enables the detection of internal chemical variation associated with artificial ripening. Using this method requires additional hardware, and it may increase the complexity of system.

D. Fusion Model:
To improve the accuracy of detecting chemically ripened fruits, the Fusion model combines the information of fruit images and sensor data. Here, image-based data provide information about external features like colour, texture, and surface appearance. Sensor-based data provides information about internal changes occurring during the ripening process. First RGB images of fruits are collected, and at the same time, sensor data is also collected. Then, the collected data are cleaned and normalised so they can be compared and processed successfully. After that, important features are extracted from images, such as colour, texture, and surface appearance, and from sensor data, such as chemical changes. These data are combined into a single dataset. The combined data are then given to a machine learning model. And finally, the trained model detects whether the fruit is naturally ripened or chemically ripened [10]

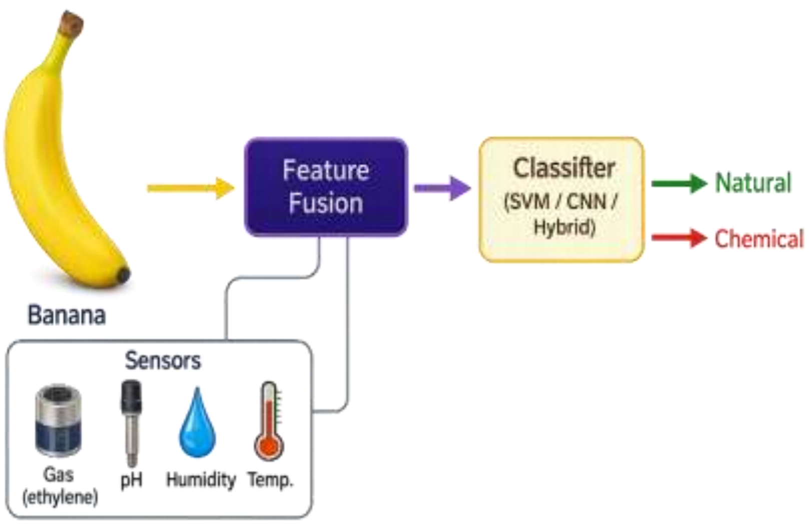

Fig. 4 Fusion Model

Mathematical Validation
Feature Fusion: The following equation was created by the author. The Equation shows merging of the features extracted from fruit images and sensor data.

$$F = [F_{image}, F_{sensor}]$$

Weighted Feature Combination: It shows how information from fruit images and sensor data is combined.

$$F_{combined} = \alpha F_{image} + \beta F_{sensor}$$

Decision Fusion (Model Output): For accurate prediction, the method combines output from image-based and sensor-based models.

$$Y = w_1 \cdot Y_{image} + w_2 \cdot Y_{sensor}$$

Where:

F_{image}→ Features extracted from images
F_{sensor}→ Features from sensor data
α, β→ Weight factors (importance of each feature type)
$F_{combined}$→ Final fused feature vector
Y_{image}, Y_{sensor}→ Predictions from individual sources
w_1, w_2→ Weights for decision fusion
Y→ Final classification output

E. Multispectral Imaging Method:

It is a modern method for detecting chemically ripened fruits. Here, a multispectral camera is used for capturing images at several wavelengths of light including visible and near infrared regions. These additional wavelengths provide useful information such as internal condition and chemical properties of the fruit. The captured data is pre-processed to remove noise and normalize intensity values across spectral bands. These spectral images are then combined to form a multi-channel input. Feature extraction is performed automatically by deep learning models such as CNNs, which learn spatial and spectral patterns associated with ripening. The model is trained using labelled data to distinguish between naturally and chemically ripened fruits. Finally, the trained network classifies new samples based on learned spectral features, providing high accuracy due to its ability to capture internal variations [11].

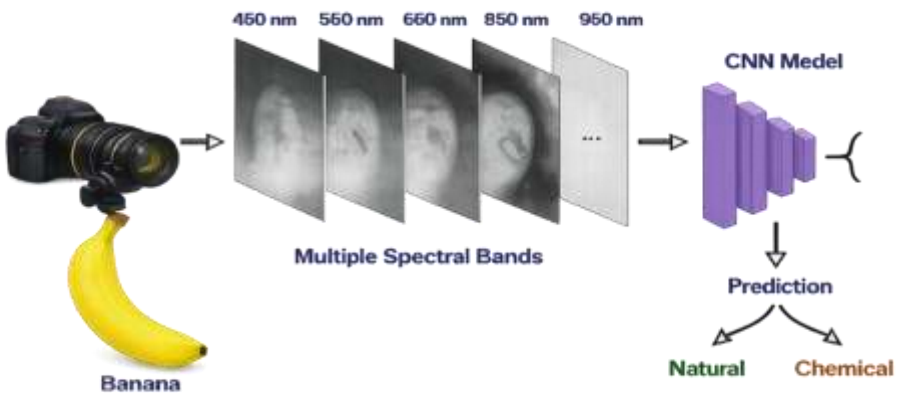

Fig. 5 Multispectral imaging Method

Mathematical Validation

Multispectral Image Representation:

This is a standard representation used in multispectral imaging, hyperspectral imaging, remote sensing, spectral image analysis.

Components:

$$I(x, y, \lambda)$$

Multi-Channel Input Formation: This equation represents the stacking of multiple spectral band images into a single multi-channel input tensor for CNN processing. This representation is formulated by the author to describe the multispectral data structure.

$$X = [I_{\lambda_1}, I_{\lambda_2}, \ldots, I_{\lambda_n}]$$

CNN Feature Extraction: This equation performs convolution between: multispectral input, convolution kernel/filter. It extracts spectral features, spatial patterns, texture variations, chemical ripening signatures.

$$O_{i,j} = \sum_m \sum_n X_{i+m,j+n} \cdot K_{m,n}$$

Classification (SoftMax Output): This is a standard classification equation used in neural networks. This equation converts CNN output scores into probabilities for classification. It determines naturally ripened fruit probability, chemically ripened fruit probability.

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

Where:
$I(x, y, \lambda) \rightarrow$ Image intensity at position $(x, y)$and wavelength λ
$X \rightarrow$ Multi-channel spectral input
$K \rightarrow$ Convolution kernel
$O_{i,j} \rightarrow$ Extracted feature map
$P(y_i) \rightarrow$ Probability of class i

F. Image Processing Method:
Image processing method is commonly used method for differentiating between naturally and chemically ripened fruits. It works on visual features of the fruits such as colour, texture, and shape. This technique is simple, requires low computational power and is more cost- effective. This method has a limited ability to detect chemically ripened fruits because it depends on external appearance of the fruits [12].
In this approach fruit images are captured using camera under controlled or natural lighting conditions. The captured images are then pre-processed to remove noise and improve image quality. Following preprocessing, segmentation is performed for isolation of the fruit region from the background. Feature extraction is carried out with analysing visual properties such as colour intensity, texture patterns, and shape characteristics. Extracted features are used for classification purpose using thresholding or rule-based decision methods to decide if fruit is naturally or chemically ripened [13].

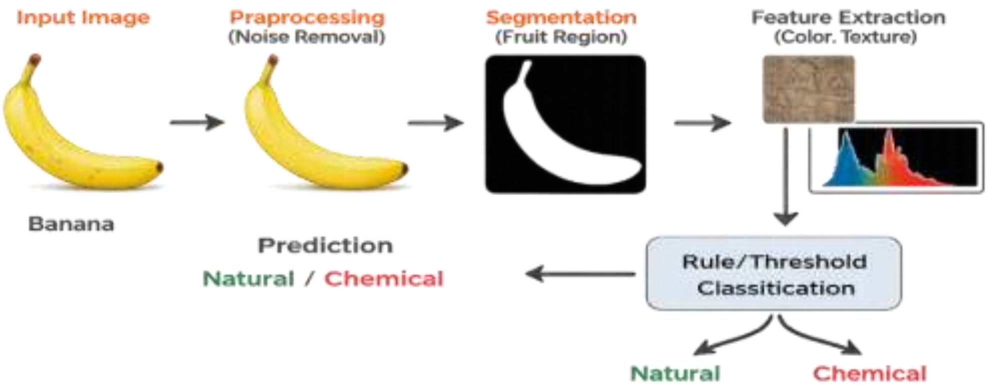

Fig. 6 Image Processing Method

Mathematical Representation:
Image Representation: This is a standard inbuilt image representation notation. This notation represents the image intensity value at pixel position (x, y). It is the most fundamental representation used in digital image processing, computer vision, image analysis.$f(x, y)$
Thresholding Operation: This is a standard thresholding equation widely used in image segmentation. This equation performs image segmentation by converting the image into: foreground (fruit region), background. Pixels above threshold $T$are assigned value 1, others 0. his helps isolate the fruit region for feature extraction.

$$g(x, y) = \begin{cases} 1 & f(x, y) > T \\ 0 & otherwise \end{cases}$$

Colour Feature (Mean Intensity): This is a standard statistical feature extraction equation. This equation calculates the average intensity value of image pixels. It is commonly used for colour analysis, brightness estimation, feature extraction. Mean colour intensity helps differentiate ripeness stages based on fruit surface colour.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} f(x_i, y_i)$$

Texture Feature (Variance): This is a standard statistical equation. This equation computes variance, which measures intensity variation or texture roughness in the image. It is widely used in texture analysis, image statistics, pattern recognition. Texture variation helps identify abnormal surface patterns caused by chemical ripening.

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (f(x_i, y_i) - \mu)^2$$

Where:
$f(x, y) \rightarrow$ Pixel intensity at position (x, y)
$T \rightarrow$ Threshold value
$g(x, y) \rightarrow$ Segmented output image
$\mu \rightarrow$ Mean intensity (color feature)
$\sigma^2 \rightarrow$ Variance (texture feature)
$N \rightarrow$ Number of pixels
Image processing methods provide a simple and computationally efficient approach for fruit classification; however, their reliance on surface-level features limits their ability to accurately detect chemically ripened fruits.

III. Proposed Thermal Imaging–Based Method:

This proposed method is used to detect chemically ripened fruits without destroying the fruit. It does not capture colour and appearance of the fruit, it captures the temperature distribution on the fruit. During the ripening process, several chemical and biological changes take place inside the fruit. These internal changes affect the way heat is distributed across the fruit surface. Fruits are ripened using different chemicals and it produces different temperature distributions. It is different from the naturally ripened fruits' heat distribution. These differences may not be visible to human, but they can be detected by using thermal imaging.

In this method, thermal images are captured using a thermal camera. Thermal camera represents the temperature distribution on the fruit surface. After capturing, they are pre-processed to improve fruit quality. Feature extraction is then performed on the processed images. This can be done by analysing thermal properties such as temperature distribution and gradients or by using CNN models to learn features automatically. The extracted information is used to train a classification model. The model learns the differences between natural and chemical ripening patterns. During testing, new thermal images are provided to the trained model. Based on the learned thermal features, the model classifies the fruit as naturally ripened or chemically ripened. The system can also be deployed on edge devices for real-time detection.

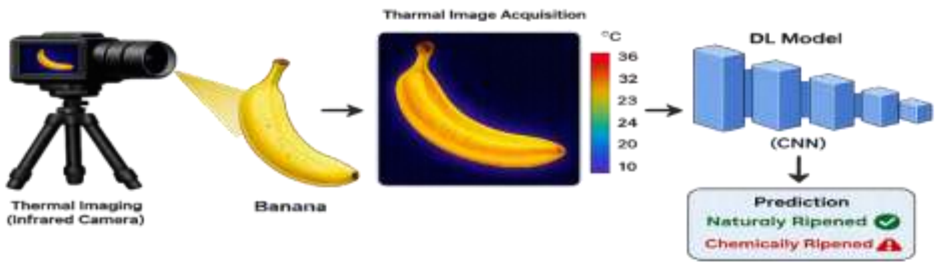

Fig. 7 Thermal Imaging Based Method

Mathematical Representation:

Thermal Image Representation: This is a standard scientific representation. This notation represents the temperature value at pixel position (x, y)in a thermal image. It is commonly used in thermal imaging, infrared image processing, thermography analysis.

$$T(x, y)$$

Temperature Variation (Thermal Feature): This is a standard thermal analysis equation commonly used in thermography and heat distribution studies. This equation measures temperature spread across the fruit surface. Chemically ripened fruits may show abnormal thermal distribution due to: uneven chemical reactions, altered respiration, moisture variation.

$$\Delta T = T_{max} - T_{min}$$

Mean Temperature: This is a standard statistical feature extraction equation. This equation computes the average temperature across the fruit surface. Average temperature may vary between naturally ripened fruits, chemically ripened fruits.

$$\mu_T = \frac{1}{N}\sum_{i=1}^{N} T(x_i, y_i)$$

Thermal Gradient (Spatial Variation): This is a standard vector calculus/image processing equation widely used in thermal imaging, edge detection, spatial analysis. This equation measures spatial temperature change across the fruit surface. It identifies hotspots, uneven heat patterns, thermal edges, ripening irregularities.

$$\nabla T = \left(\frac{\partial T}{\partial x}, \frac{\partial T}{\partial y}\right)$$

CNN-Based Classification: This is a conceptual representation formulated by the author for the proposed framework.

$$Y = f(T(x, y))$$

Where:
$T(x, y)$→ Temperature at pixel location
ΔT→ Temperature difference across fruit surface
μ_T→ Average temperature
∇T→ Temperature gradient (heat variation pattern)
Y→ Predicted class (Natural / Chemical)
N→ Number of pixels

The proposed thermal imaging-based method enables non-destructive detection of chemically ripened fruits by capturing internal thermal variations, offering a robust and illumination-independent alternative to conventional imaging techniques.

IV. Comparative Results

Table 1: Comparison between all methods

Sr. No.	Method	Input Data	Working	Accuracy	Advantages	Limitations
1	Traditional Machine Learning (SVM, KNN)	RGB Images	Extract colour & texture manually, then classify	~85–90%	Simple, low cost	Lower accuracy, manual effort
2	Neural Networks (ANN/CNN)	RGB Image Data	Learns features automatically from images	~90%	Better accuracy, automatic learning	Needs more data
3	Sensor-Based Method (pH, Gas, Humidity)	Sensor Data and RGB Data	Uses chemical & environmental data for detection	~90%	Detects hidden changes	Needs extra hardware
4	Fusion Model (Image and Sensors)	Image and Sensor Data	Combines both data types for better decision	~90%	High accuracy	Complex setup
5	Image Processing	RGB Images	Uses simple features like colour & edges	~92%	Easy to implement	Low accuracy
6	Multispectral Imaging and DL	Multispectral Data	Uses multiple wavelength images to detect internal changes	>95%	Very high accuracy	Expensive, complex

7	Proposed Thermal Imaging	Thermal Images	Detects temperature patterns on fruit surface	>96%	Non-destructive, cost-effective	Needs proper calibration

Above table represents comparison between different methods which are used to detect chemically ripened fruits. Each method uses different types of data and techniques and they are different in terms of accuracy, cost and complexity. This comparison helps to understand the methods and limitations of each method. Traditional machine learning method uses RGB images and it manually extracts features such as colour, textures and shape. This method provides moderate accuracy but it is less effective than modern approaches. Deep learning methods automatically extract features from fruit images and achieve higher accuracy. But it requires large dataset and more computing power. To detect internal changes, Sensor-based method use information such as gas concentration, pH value, humidity, and temperature. To increase detection performance, Fusion-based method combines image and sensor data but it increases system complexity. Multispectral imaging provide higher accuracy but it requires expensive equipment. Proposed Thermal imaging method is non destructive method that uses temperature patterns to identify ripening, and it gives high accuracy.

V. Conclusion

Artificial Intelligence and Deep learning have improved techniques that have improved the detection of chemically ripened fruits compared to traditional methods. Traditional machine learning methods are simple and cost-effective but mainly rely on surface features. Deep learning models provide better accuracy by automatically learning important patterns from images. Sensor-based methods can detect internal chemical changes but require additional hardware. Fusion models combine image and sensor data to improve detection performance although they increase system complexity. Multispectral imaging achieves high accuracy by capturing information beyond visible light but involves expensive equipment. Thermal imaging has emerged as an effective non-destructive technique for fruit ripeness detection. It uses temperature distribution patterns to identify differences between naturally and chemically ripened fruits. Comparative analysis shows that thermal imaging-based approaches can achieve higher accuracy than many conventional methods. The proposed thermal imaging framework provides a reliable solution for fruit quality assessment. Future work should focus on Explainable AI and larger dataset for practical agricultural applications.

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