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RESEARCH

# Non-destructive Classification of Harvested *Terung Asam* (*Solanum lasiocarpum* Dunal.) Utilising Thermal Imaging and Machine Learning Across Different Storage Days

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**Abstract**

Thermal imaging has non-invasive qualities which have attracted the interest of researchers as it could improve agricultural methods, especially in the field of fruit classification based on their storage duration. This study explores the potential of thermal imaging and machine learning for the non-destructive classification of *Terung Asam* (*Solanum lasiocarpum* Dunal.) fruit at different storage durations. Nine thermal image parameters were analysed to monitor changes in fruit characteristics over day 0, day 7, day 14, day 21 and day 28. Key thermal image parameters, including major axis length (MajorAL), maximum intensity (MaxInt) and mean value within the region of interest (MeanROI), exhibited significant variations throughout the storage period, reflecting changes in fruit morphology and surface temperature associated with ripening and moisture loss. Correlation analysis revealed strong correlation between these parameters. The strongest correlation was found between MajorAL and MinorAL ($r = 0.967$) and between MaxInt and MajorAL ($r = 0.962$). Five machine learning models, i.e. Fine Decision Tree, Medium Decision Tree, RUSBoost Tree, Boosted Tree and Fine k-Nearest Neighbour (kNN), were evaluated for classification performance. Fine and Medium Decision tree achieved the highest classification accuracy at 86.7%, effectively distinguishing *Terung Asam* fruits based on storage duration. This study underlines thermal imaging as a reliable, non-invasive tool for post-harvest classification of *Terung Asam* fruit, improving storage monitoring and reducing waste. Future research should focus on deep learning integration to enhance classification performance over extended storage periods.

**Keywords** Machine learning · Post-harvest · Storage · *Solanium lasiocarpum* Dunal · Thermal imaging

## Introduction

*Solanum lasiocarpum* Dunal., which is also called sour eggplant or *Terung Asam*, is a crucial crop that belongs to the state of Sarawak, renowned for its market value and diverse health benefits (Soon & Ding, 2021). It is recognised for its functional food properties, which include flavonoids and phenolic compounds that are high in antioxidants and provide various health benefits including free radical scavenging activity (Oszmianski et al., 2014; Rahman et al., 2019; Soon & Ding, 2021). *Terung Asam* is a promising crop for local farmers due to its high yield potential, which can reach up to 20 tons per hectare and they usually fetch a price of up to RM10 per kilogram (Sman, 2017). The *Terung Asam* fruit is often classified based on physical characteristics such as weight, colour, size, firmness and chemical traits influenced by storage length. Since *Terung Asam* fruit has distinctive attributes, it is necessary to ensure that the harvest

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is separated according to their storage duration, fruit quality and customer preferences.

Current quality evaluation techniques depend on physical and chemical characteristics, including weight, firmness, colour and chemical composition. Although these approaches are efficient for preliminary assessments, they are labour-intensive and demand skilled workers and specialised equipment such as gas chromatography-mass spectrometry (GCMS) and high-performance liquid chromatography (HPLC) and various physicochemical evaluations (Hazimah et al., 2023; Herqash et al., 2024; Mohd Ali et al., 2022). These conventional methods lack real-time accuracy, particularly during the storage phase when fruit experiences physiological alterations. Detecting internal changes, such as moisture loss and metabolic activity, remains challenging, as these factors may not consistently correlate with exterior visible signs like bruising or colour changes. Consequently, there is a need for more effective and non-destructive techniques to evaluate fruit quality throughout the storage duration.

Although *Terung Asam* exhibits noticeable colour alterations during ripening, surface coloration does not consistently reflect interior physiological changes, like respiration rate, moisture loss or metabolic activity, which are important indicators of fruit quality during storage. Merely depending on digital imaging could therefore be insufficient. Thermal imaging provides a non-invasive method for identifying minute variations in temperature on the fruit's exterior, revealing interior alterations such as moisture loss and metabolic processes (Mohd Ali et al., 2020, 2024). This method has been effectively utilised in multiple crops, including jujube (Dong et al., 2022) and strawberries (Guo et al., 2022), for the identification of bruising (Arango et al., 2021), disease indicators (Mahanti et al., 2022) and ripeness stages. Nonetheless, its utilisation in niche fruits such as *Terung Asam* remains unexplored. In advanced storage stages, where visible indicators stabilise despite ongoing interior deterioration, thermal imaging is particularly advantageous. The integration of machine learning algorithms improves categorisation accuracy by examining temperature distribution, providing profound insights into internal quality alterations and augmenting digital imaging for more comprehensive post-harvest evaluations (Arango et al., 2021; Hespeler et al., 2021).

Machine learning approach which includes k-Nearest Neighbour (kNN), Random Forest and Decision Trees have been effectively utilised in agricultural data, providing high precision in assessing fruit quality, identifying defect and predicting moisture content (Keramat-Jahromi et al., 2021; Sangeetha et al., 2023). These algorithms, when coupled with thermal imaging, can yield significant insights into fruit quality by examining complex multivariate information. Studies have shown that Random Forest and kNN algorithms, when utilised on thermal and RGB measurements, can accurately categorise fruit age and texture, hence improving non-invasive quality assessment (Sangeetha et al., 2023).

Despite the expanding research in thermal imaging and machine learning for fruit quality evaluation, a significant gap exists in the application of these technologies to *Terung Asam*, especially with the classification of fruit according to different storage periods. Prior research has predominantly concentrated on prevalent crops such as pineapples (Mohd Ali et al., 2022), bananas (Waluyo et al., 2023) and mangoes (Naik & Patel, 2017) but there is a lack of studies investigating the application of thermal imaging and machine learning for quality classification relative to storage duration. This study seeks to address this gap by examining the efficiency of thermal imaging integrated with machine learning techniques to categorise *Terung Asam* according to its storage period.

The specific objectives of this study were as follows: (1) to determine the thermal image parameters of *Terung Asam* fruit over various storage durations, and (2) to evaluate the performance metrics of machine learning algorithms based on the thermal image parameter features. This study enhances the understanding of *Terung Asam* and highlights the reliability of non-destructive methods such as thermal imaging and machine learning for post-harvest quality assessment. By using these technologies, the study provides scalable solutions for improving fruit grading, reducing waste and supporting market-driven quality control in Sarawak's agriculture sector.

## Materials and Methods

### Sample Collection and Storage Conditions

A total of 150 *Terung Asam* fruits were acquired from Agricultural Market Bandar Riyal in Samarahan, Sarawak (N1°27′30.4″, E110°24′36.7″) through direct coordination with a farmer who also serves as a seller, ensuring immediate access post-harvest. The fruits were selected based on the absence of physical flaws, and uniformity in skin texture, colour and hardness (Soon & Ding, 2021). The fruits were gently cleaned using a kitchen towel to remove surface dirt and moisture before the experiment. To maintain consistent conditions, the fruits were kept at a uniform temperature in a controlled room at 25 ± 2 °C and 65–75% relative humidity for a period of 28 days and categorised into five storage durations, i.e. day 0, day 7, day 14, day 21 and day 28, with 30 samples in each category. The ripeness of *Terung Asam* was standardised based on skin colour, with all fruits selected for the study being green at the initial storage day (day 0) (Arumugasamy & Antonidoss, 2023; Soon et al., 2023). Each fruit was cleaned again before being stored in the laboratory in an uncoated box without plastic or wax lining to allow for natural airflow and avoid moisture buildup that could affect temperature readings.

## Thermal Imaging Setup

The FLIR TG165-X camera was used to capture thermal images. It has an IR resolution of 80 × 60 pixels and a thermal sensitivity (NETD) of less than 70 mK which enables the detection of minute temperature differences. The temperature measurement range of the camera spans from − 25 to 300 °C, with accuracy varying across different temperature ranges: ± 1.5 °C from 50 to 100 °C, ± 2.5 °C from 0 to 50 °C and 100 to 300 °C, and ± 3 °C from − 25 to 0 °C. The camera features a field of view (FOV) of 51° × 66° and a distance-to-spot ratio of 24:1, allowing for effective measurement of small targets at a distance. Prior to imaging, the emissivity setting was adjusted to 0.95, a value commonly used for fruits and vegetables in thermal imaging. This is consistent with prior studies showing that apple skin emissivity has been calibrated at 0.96 in active thermography studies (Veraverbeke et al., 2006), and typical emissivity for horticultural products has been reported as 0.94 ± 0.04 (Hellebrand et al., 2001). Similarly, Lipińska et al. (2022) applied an emissivity setting of 0.95 in their thermal imaging study on apples, supporting the use of this standard value for comparable fruit surface analysis. The process of obtaining thermal images was conducted in a controlled laboratory setting at room temperature (25 ± 2 °C), as shown in Fig. 1 (Mohd Ali et al., 2021). Thermal images were obtained for 30 repetitions on various storage days of *Terung Asam*, specifically on day 0, day 7, day 14, day 21 and day 28. All thermal images were taken in a dark room under controlled laboratory conditions (25 ± 2 °C, 65–75% RH) to eliminate infrared interference and maintain thermal consistency. The fruit samples were placed on a non-reflective holder to reduce background noise, and each was imaged from a top view. The camera was allowed to warm up for 5 min prior to use to ensure thermal stability. The images were obtained at a fixed vertical distance of 60 cm from the fruit which ensured consistent thermal readings. The repeated imaging guaranteed the collection of adequate data for each ripeness level, enabling thorough analysis and precise classification of *Terung Asam* over various storage durations by thermal image parameters.

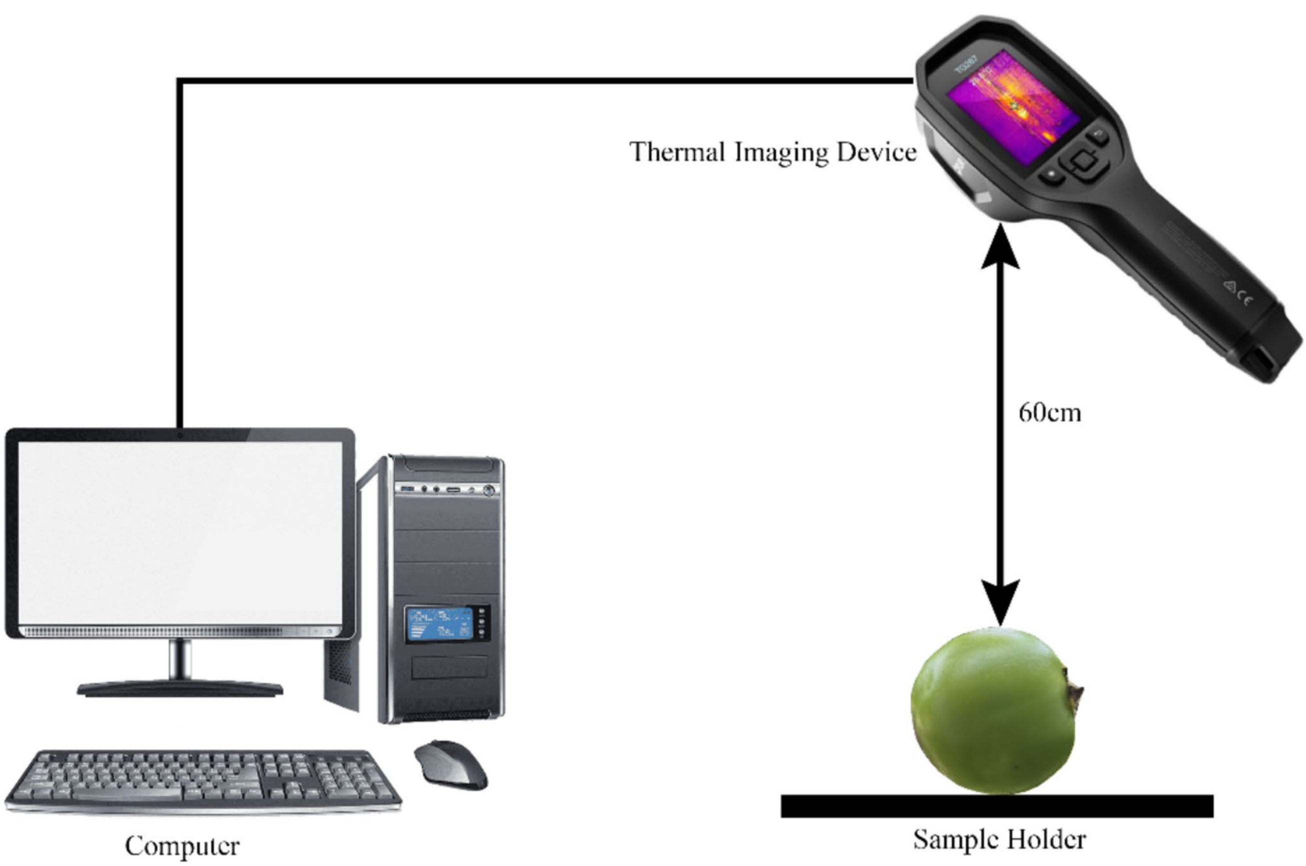


**Fig. 1** Schematic representation of thermal image acquisition setup for *Terung Asam* fruit classification

### Thermal Image Parameter Extraction

The thermal images of *Terung Asam* fruit at various storage durations were analysed using MATLAB software (Version R2020a, The MathWorks, USA). The thermal images were transformed into grayscale, and background noise was eliminated by determining the average pixel value of each image's region of interest (ROI) and applying Otsu's thresholding method (Mohd Ali et al., 2024). The binary image generated after extracting the ROI was further improved by applying a Gaussian filter to enhance the quality of the image (Fig. 2). The fruit ROI was delineated on the thermogram using Otsu's thresholding, producing connected regions within the fruit mask. By default, geometric parameters represent region-level measurements within the thermal ROI and are expressed in pixels. These parameters describe image-based regions rather than calliper measurements of the entire fruit. In this study, intensity refers to the surface temperature derived from thermograms after emissivity calibration and camera stabilisation, distinguishing it from optical brightness in visible light images. Temperature parameters were computed within the fruit ROI, where ambient referencing would not affect the observed thermal patterns.

The process of feature extraction from the segmented images was carried out by analysing the pixel values. This included determining the major axis length (MajorAL), minor axis length (MinorAL), perimeter (Peri), maximum intensity (MaxInt), minimum intensity (MinInt), average intensity (AveInt), mean value within the region of interest (MeanROI), maximum value within the region of interest (MaxROI) and minimum value within the region of interest (MinROI). The parameters MajorAL, MinorAL and Peri are geometric descriptors derived from the fruit's thermal geometry, representing the shape and size of the thermal boundary. These variables are not temperature-based features but are extracted from the thermal contour, which reflects the

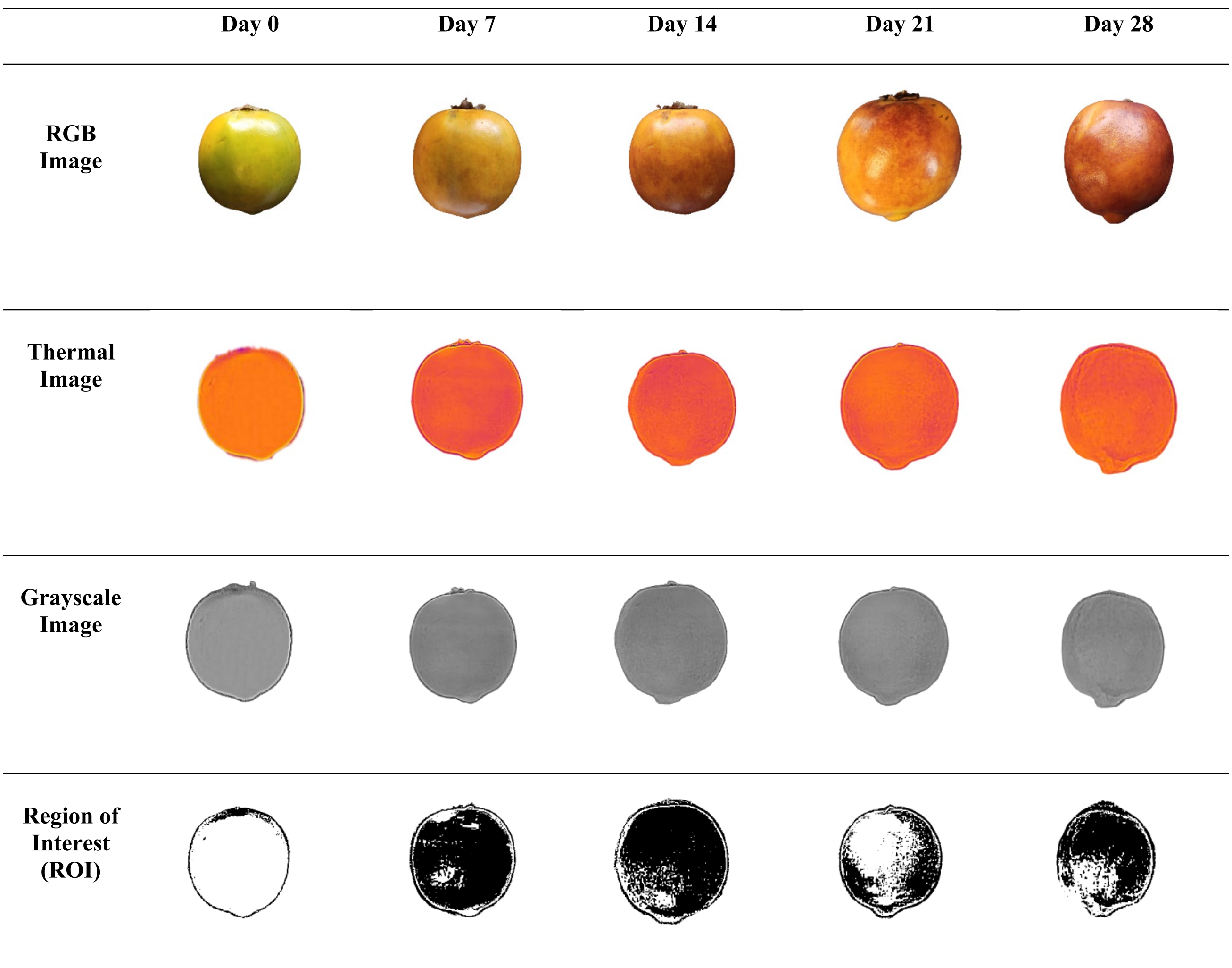


**Fig. 2** Thermal image analysis using image segmentation process

fruit's surface area and the spatial distribution of temperature across its surface. Meanwhile, the temperature-based features, including MaxInt, MinInt, AveInt and others, were extracted from the temperature variation across the ROI. Specifically, the AveInt was computed as the mean of all pixel values within the ROI, representing the overall thermal emission of the fruit surface. These thermal metrics were subsequently utilised to establish relationships between image-derived parameters and fruit quality attributes such as ripening stages, storage effects and post-harvest quality (Mohd Ali et al., 2024; Zárate et al., 2023).

## Machine Learning Algorithms

Five different machine learning algorithms were utilised to classify *Terung Asam* fruits based on their physiological changes at different days based on the image parameters including Fine Decision Tree, Medium Decision Tree, RusBoost Tree, Boosted Tree and Fine kNN. All of the machine learning algorithms were built using MATLAB (Version R2020a, The MathWorks, USA) in order to discriminate *Terung Asam* based on various storage durations stages (Fig. 3).

To ensure a reliable evaluation, the dataset was randomly split into 70% for training and 30% for testing. Model performance was assessed using accuracy, precision, recall and F1-score, all derived from the corresponding confusion matrices. The Boosted Tree, RUSBoost Tree and Fine kNN algorithms were selected for their superior classification performance and ability to handle the nuanced thermal image data effectively.

### Decision Tree

Decision Tree classifiers are regarded to be a standout of the most well-known methods of data classification representation of classifiers (Jijo & Abdulazeez, 2021). Decision Tree methods are distinguished by their capacity to correlate independent factors with class outcomes via repeated data partitioning. They function by dividing data into branches that signify potential outcomes based on independent variables. This division persists until all items within a branch are

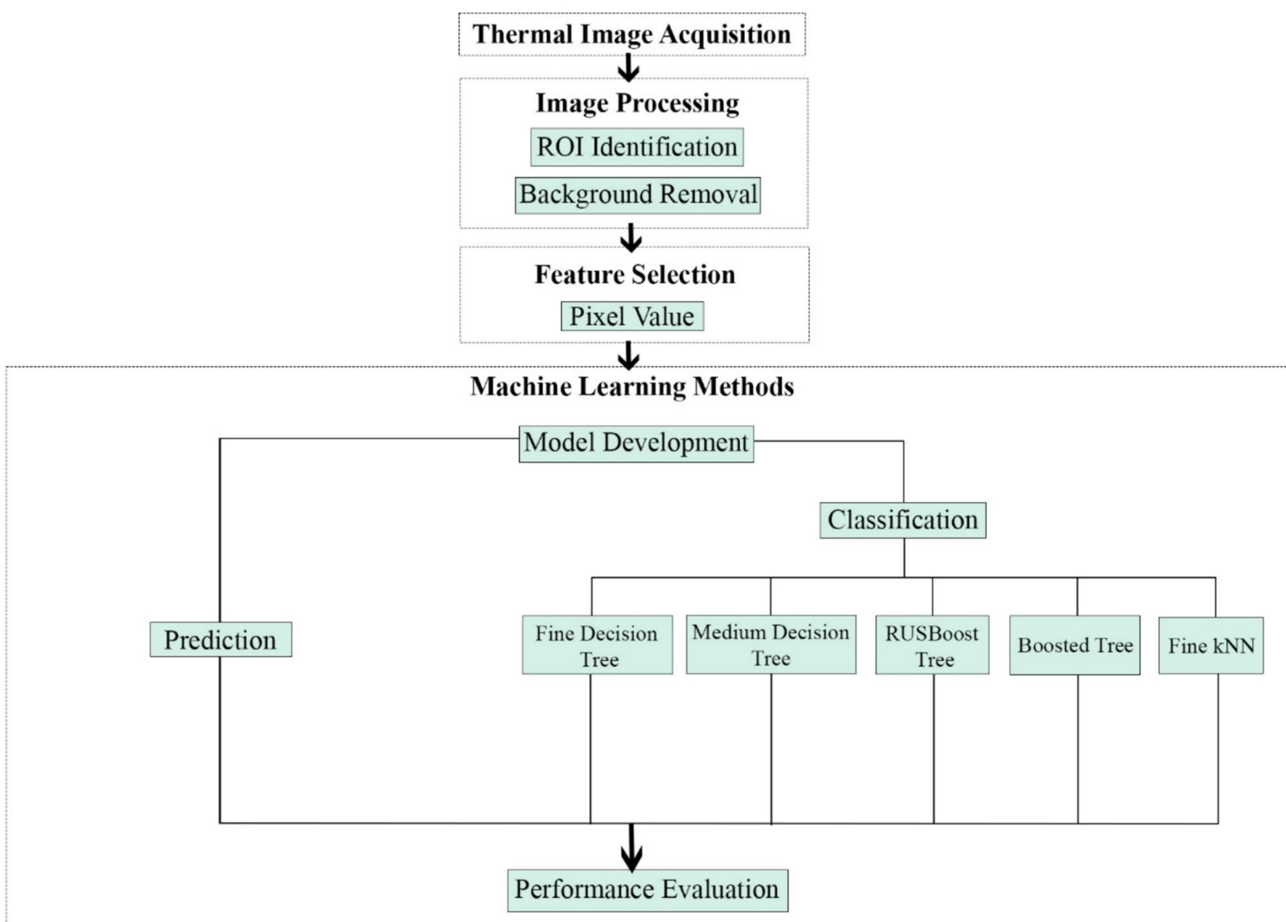


**Fig. 3** Flowchart for classifying *Terung Asam* over different storage durations using infrared thermal imaging and machine learning techniques

classified under the same label. The tracing of paths is made easier by the tree structure that comprises of nodes, root and leaves, which leads to classification decisions. Therefore, it is preferred because it yields clear hierarchical relationships (Song & Lu, 2015). The Decision Tree classifiers that are usually used in practical applications can be divided into three categories, i.e. Fine Decision Tree, Medium Decision Tree and Coarse Decision Tree, which are commonly utilised in practical applications (Özbay & Çinar, 2019). In this study, Fine and Medium Decision Trees were used to interpret thermal imaging data. The data records temperature distribution. It is a decisive aspect in identifying various types of *Terung Asam* fruit based on various storage durations, by striking a balance between accuracy and complexity.

**Fine Decision Tree** The Fine Decision Tree method is refined so that it could identify significant differences in features like the ebb and flow in temperature due to thermal imaging (Jiang et al., 2023). This method yields high precision and fine segmentation in the process of classifying the thermal images of *Terung Asam* fruit over the course of numerous different storage durations, allowing a large number of splits. This extent of granularity benefits datasets whereby differences in colour and temperature are important to the process of classification (Mohd Ali et al., 2020).

**Medium Decision Tree** The outcome from the median decision tree algorithm observes a balanced model complexity and generalisability. This is achieved by the restriction in the number of splits that helps to sustain the robustness in the model and reduce the possibility of overfitting (Balcan & Sharma, 2024). This regulated procedure benefits the thermal imaging data analysis because variations in environmental aspects could result in inconsistency or noise (Kaur et al., 2024). When the number of splits is reduced, it enhances the generalisation capability of the model, which results in performance that is consistent throughout various storage durations as well as varying and environmental conditions (Balcan & Sharma, 2024). The Medium Decision Tree fits this research that has an objective to categorise which *Terung Asam* by basing upon numerous different durations of storage through infrared thermal imaging.

#### RusBoost Tree

The imbalances in data set are addressed by the RusBoost Tree method when combined with Random Under-Sampling (RUS) and Boosting. The examples of imbalances are like the uneven representation of duration of storage. In tasks where data imbalance is challenging, like the analysis of fruit storage and disease detection in fruit, this method comes in extremely handy and is used extensively (Zhang & Gionis, 2023). Through the process of training various weak learners on data that is resampled which these classes that are under-represented, the RusBoost Trees drastically increases the performance of classification of less-represented storage durations (Seiffert et al., 2010). This process is crucial to make sure that the classification of the *Terung Asam* fruits at rare storage durations is accurate. This is especially important for datasets that have uneven storage periods representation. As a result of this process, all classes would be taken into consideration during the analysis and predictive efficacy and accuracy can be retained.

#### Boosted Trees

Boosted Trees uses ensemble learning in the process of improving model precision (Maniwa et al., 2024). Numerous decision trees are being trained successively, whereby every iteration would be addressing the mistakes made by the previous iteration (Schapire, 2013). The methods ability in managing non-linear relationships between variables renders it a regression issues and classification (Dong et al., 2023; Friedman, 2001). This research used Boosted Trees in categorising the phases of maturity of *Terung Asam* through the use of thermal imaging data. In identifying subtle thermal characteristics that shows different storage duration, this algorithm has been proven to be proficient. This is achieved by the algorithm using its capacity in focusing on cases that are difficult to categorise. By prioritising challenging samples during training, the model adapts to varied thermal patterns over time, assuring resilient classification across various stages.

#### Fine k-Nearest Neighbours (kNN)

That is a version called the Fine kNN, which is a variation of the kNN algorithm. In this version, the number of neighbours (K) is set to a lower value. As a result of it, the model is more sensitive to local variations in the data (Iwan Sudipa, et al., 2024). This research uses the Fine kNN in categorising *Terung Asam* across various duration of storage through the use of thermal imaging data. This method computes the distance between all training data points and test data in order to identify the nearest neighbours (Qiu et al., 2018). By basing on the majority class of these neighbours, the test data classification is determined.

### Data Analysis and Model Evaluation

The analysis of variance (ANOVA) was used to study the extensive variations in the characteristics of thermal imaging at numerous durations of storage of *Terung Asam*. Tukey's test was used to compare the post hoc at a significance threshold level of < 0.05. SPSS software (IBM SPSS ver. Statistic 27.0.1.0) was used to carry out the statistical analyses. In every experiment of classification, different machine learning models' performances were evaluated by computing the mean accuracy.

For machine learning classification, the thermal image dataset was randomly split into 70% for training and 30% for testing using stratified random sampling to ensure balanced representation across all storage durations. The classification performance of each machine learning model was evaluated by computing the mean accuracy, along with other critical metrics derived from the confusion matrix as tabulated in Table 1 (Mohd Ali et al., 2022; Said & Joshi, 2024).

These metrics provided a comprehensive view of model performance and robustness. Visualisation tools such as feature distribution plots and scatter graphs were used to observe the variability of thermal imaging data across different storage intervals. Crucial thermal parameters that affect classification performance was identified by analysing feature relevance. The categorisation models were especially assessed for the ability in achieving high accuracy in tests to ensure reliable storage time classification.

## Results and Discussion

### Changes of Thermal Image Parameters

Using feature extraction from infrared thermal images of the *Terung Asam*, relevant thermal parameters were selected to provide an in-depth understanding of physiological changes occurring throughout storage. The analysis aimed to correlate these parameters with compositional and textural alterations of the fruit and access their applicability for classification using machine learning techniques.

Table 2 presents the ANOVA results summarising the mean of thermal characteristics for *Terung Asam*, including MinInt, MajorAL, Peri, MaxInt, MinorAL, AveInt, MeanROI, MaxROI and MinROI. These values represent per-image distributions of segmented thermal regions expressed in pixels, and describing geometric and temperature-related properties of the fruit. During early storage, fruits often exhibited moisture-related reductions in turgor without notable changes in thermal geometry, particularly in nearly spherical samples with minimal mass loss. Similar

**Table 1** Evaluation metrics and corresponding formulas used for machine learning model performance

| Metric | Formula | Description |
|---|---|---|
| Accuracy | (TP + TN)/(TP + TN + FP + FN) | Proportion of total correct predictions out of all cases |
| Precision (PPV) | TP/(TP + FP) | Proportion of true positives among predicted positives |
| Recall (TPR) | TP/(TP + FN) | Proportion of true positives among actual positives |
| F1-Score | 2 × (Precision × Recall)/(Precision + Recall) | Harmonic mean of precision and recall |

*TP* true positives, *TN* true negatives, *FP* false positives, *FN* false negatives

**Table 2** Average values of image parameter of *Terung Asam* from different storage days

| Image parameter | Day | | | | |
|---|---|---|---|---|---|
| | 0 | 7 | 14 | 21 | 28 |
| MajorAL | 8.675 ± 7.649a | 444.019 ± 14.545d | 440.882 ± 14.988d | 167.117 ± 212.827b | 276.046 ± 197.756c |
| MinorAL | 3.930 ± 3.600a | 298.794 ± 24.052c | 293.774 ± 9.425c | 167.117 ± 212.827b | 196.665 ± 140.730b |
| Peri | 25.686 ± 31.577a | 2149.333 ± 797.747b | 3550.333 ± 1537.658c | 1414.667 ± 1857.096b | 1711.400 ± 1723.889b |
| MaxInt | 0.550 ± 0.022a | 0.865 ± 0.016c | 0.812 ± 0.036c | 0.640 ± 0.132b | 0.676 ± 0.104b |
| MinInt | 0.536 ± 0.007a | 0.532 ± 0.004abc | 0.527 ± 0.007c | 0.528 ± 0.011bc | 0.533 ± 0.010ab |
| AveInt | 0.542 ± 0.006a | 0.540 ± 0.005a | 0.539 ± 0.002a | 0.539 ± 0.008a | 0.543 ± 0.007a |
| MeanROI | 0.572 ± 0.002a | 0.566 ± 0.009b | 0.570 ± 0.005ab | 0.558 ± 0.010c | 0.569 ± 0.006ab |
| MaxROI | 0.879 ± 0.014a | 0.865 ± 0.023a | 0.812 ± 0.036b | 0.809 ± 0.008b | 0.831 ± 0.079b |
| MinROI | 0.537 ± 0.007a | 0.532 ± 0.004abc | 0.527 ± 0.007c | 0.528 ± 0.011bc | 0.533 ± 0.010ab |

Data are expressed as mean ± standard deviation. Different letters within the same row denote significant differences ($p < 0.05$)

observations in post-harvest blueberries indicated turgor loss and cellular modification without distinct external deformation at low weight loss levels (Li et al., 2021). As these geometric descriptors are derived from thermal segmentation, they primarily reflect stable morphology rather than physical deformation, consistent with prior studies linking thermal features with fruit quality (Kale & Shitole, 2023).

Physiological changes linked to ripeness ($p < 0.05$) significantly influenced all the thermal metric. The variations demonstrate the effect of ripening on surface temperature distribution during the storage, validating infrared thermal imaging as a non-destructive method for monitoring ripening (Pugazhendi et al., 2023). The strong correlation between thermal parameters and storage stages suggests their potential for differentiating ripeness levels, a foundation for further machine learning classification.

Pixel intensity variations observed across storage days reflects progressive surface compositional changes (Low et al., 2024). Although MaxInt and MinInt primarily represent surface temperature, they also correspond to underlying physiological activities such as moisture loss, metabolic activity and ripening progression. These traits describe internal tissue degradation and moisture dynamics, which are essential indicators of fruit quality (Munian 2023). Maintaining a consistent measuring distance minimises interferences such as thermal reflection and ambient temperature fluctuation, ensuring reliable within-ROI characterisation under controlled condition (Izquierdo et al., 2020).

A notable trend was noticed in the MajorAL and MinorAL, with both parameters demonstrating significant increases from day 0 to day 7, indicating an expansion of the fruit's thermal geometry. This was followed by decreases on days 14 and 21, likely reflecting reductions in thermal geometry caused by surface softening or minor shrinkage due to moisture loss. A subsequent partial increase on day 28 may signify over ripening accompanied by surface deformation. These variations are biologically realistic and often result in large standard deviations, indicating diversity in fruit size and texture within the batch. The pattern of standard deviations exceeding the mean aligns with heavy-tailed region size distribution, characterised by numerous small regions and few large ones and does not imply computational error (Ikumapayi, and Akinlabi, 2019). The Peri displayed a similar trend, peaking on day 14 before slight decline. Overall, these geometric patterns represent typical post-harvest textural changes that influence fruit classification, with the increased standard deviations reflecting natural variability in fruit traits.

Comparable findings were reported by Pieczywek et al. (Pieczywek et al., 2024), who demonstrated that laser speckle imaging parameter correlated strongly with the respiration rate of apples, revealing that variations in optical or thermal geometry are directly linked to underlying metabolic and moisture exchange processes. Their work established that non-destructive optical descriptors derived from the spatial and temporal dynamics of laser speckle relaxation serve as reliable indicators of fruit respiration and internal gas diffusion. Similarly, changes observed in *Terung Asam*'s thermal geometric parameters (MajorAL, MinorAL and Peri) likely reflect the expansion and reduction of thermal surface morphology driven by respiration induced water loss and tissue softening. Together, both studies reinforce the premise that image-based geometric and thermal traits can effectively capture physiological transitions during ripening, validating the use of infrared or optimal imaging for contactless assessment of fruit quality and maturity.

Regarding thermal parameters, MaxInt and MeanROI showed initial increase around day 7 followed by decline, validating that early ripening is associated with heightened physiological activity, namely respiration and heat emission, which gradually decreases during senescence (Gurupatham 2018; Sumriddetchkajorn & Intaravanne, 2013). Although these parameters exhibited smaller shifts than geometric ones, they still provide critical insight into respiration and internal moisture loss invisible to conventional imaging. The stability of aggregate descriptors like MeanROI intensities indicates robustness against external factors such as lighting, as thermal imaging captures emissivity-corrected temperature rather than reflected light (Urzędowski et al., 2020). Hence, thermal imaging remains as valuable complementary tools for assessing fruit quality via physiological processes like respiration and transpiration.

The unripe group on day 0 exhibited the highest mean values for MinInt (0.536), MaxROI (0.879) and MinROI (0.537). This trend likely reflects the early developmental stage of harvested.

*Terung Asam*, where limited moisture loss and minimal susceptibility to mechanical damage or disease infection were observed. Similar findings were reported in pineapples and other fruits, where early-stage samples with high internal water content maintained stable surface temperatures and uniform thermal intensity profiles, confirming that minimal moisture evaporation occurs during initial ripening phases (Mohd Ali et al., 2022). According to Kumar Gurupatham and Wiles (2019), image-derived parameters can serve as fundamental indicators of physiological processes such as moisture dynamics, respiration rate and ripening progression. In this context, MinInt represents the coolest surface zones of the fruit, with its variation indicating localised cooling effects, subtle changes in store conditions or moisture loss (Lipińska et al., 2022). Similar observations were made by Pathmanaban et al. (2023), who demonstrated that infrared thermal imaging can identify localised temperature anomalies linked to uneven ripening, disease lesions or mechanical injury, thereby supporting the use of thermal features for surface defect detection and quality classification.

Moreover, unripe fruits are generally characterised by lower respiration activity and greater structural firmness than riper ones, as observed in peaches (Pérez-López et al., 2014) and pomegranates (Fawole & Opara, 2013), where respiration rate increased progressively with ripening while mechanical strength decreased due to tissue softening and moisture loss. Collectively, these findings substantiate that the elevated MinInt, MaxROI and MinROI values at day 0 reflect low respiration activity and high turgidity typical of early stage of harvested fruits, providing a robust physiological basis for their interpretation as indicators of freshness and initial ripeness.

The ripe group of thermal images on day 7 and day 14 exhibited the highest geometric values, with MajorAL at 444.019 and 440.882 and MinorAL at 298.794 and 293.774, respectively. During these stages, *Terung Asam* entered active ripening, leading to mild deformation of the fruit's structure, texture and contour. The observed expansion in thermal geometry, reflected by increases in MajorAL and MinorAL, suggests heat surface enlargement due to cellular turgor chances, internal gas accumulation and progressive softening in parenchymal tissues. This pattern is consistent with elevated respiration activity and water redistribution within the fruit, processes that generate localised heat and alter tissue elasticity (Santoyo-Mora et al., 2019). Similar correlations between geometric or optical expansion and fruit respiration have been demonstrated using laser speckle and thermal imaging in mangoes and apples, where increased surface area and deformation corresponded to enhanced gas exchange and metabolic intensity (Naik & Patel, 2017; Pieczywek et al., 2024). These morphological adjustments are biologically plausible as fruits undergo substantial restructuring during ripening and the onset of senescence. The variation and standard deviations observed across samples reflect the natural diversity in ripening rates among fruits batch. In addition, the geometric expansion during mid-storage confirms the sensitivity of thermal imaging to physiological transitions, supporting its utility for non-destructive monitoring of ripeness and textural evolution (Lai et al., 2023; Sumriddetchkajorn & Intaravanne, 2013).

The thermal imaging parameters of the overripe group at day 21 and day 28 exhibited the strongest influence on the MinInt values, measuring 0.528 and 0.533, respectively. At these advanced storage stages, the *Terung Asam* fruit was deteriorating due to moisture loss and the peel color had transitioned to an overripe yellow, which is consistent with prolonged storage. This aligns with previous thermal imaging studies by Lipińska et al. (2022), who observed changes in surface temperature distribution and intensity in overripe apples caused by moisture loss and fungal development, supporting the observed decrease in MinInt values as an indicator of physiological degradation. In addition, thermal descriptors should be interpreted through bio thermal principle, considering the interplay between transpiration and respiration, rather than assuming that all temperature metrics directly correlate with mass or size variation. A stable surface temperature profile may emerge during over ripening once moisture and heat transfer have reached equilibrium (Hoffmann et al., 2021).

## Correlation of Thermal Image Parameters

Figure 4 shows the correlation matrix demonstrates substantial correlations among the variables. MajorAL and MinorAL exhibit a strong positive correlation at 0.967, signifying that changes in fruit shape during storage are consistent in both dimensions and denote a reliable indicator for fruit classification. These geometric features are crucial for detecting morphological changes such as softening, swelling or shrinkage across different ripeness stages. MaxInt exhibits a strong correlation with MajorAL at 0.962 and MinorAL at 0.923, indicating that fruits with greater surface dimensions tend to emit more thermal energy which is likely due to increased metabolic heat during ripening. This also emphasises the role of MaxInt as a sensitive thermal parameter

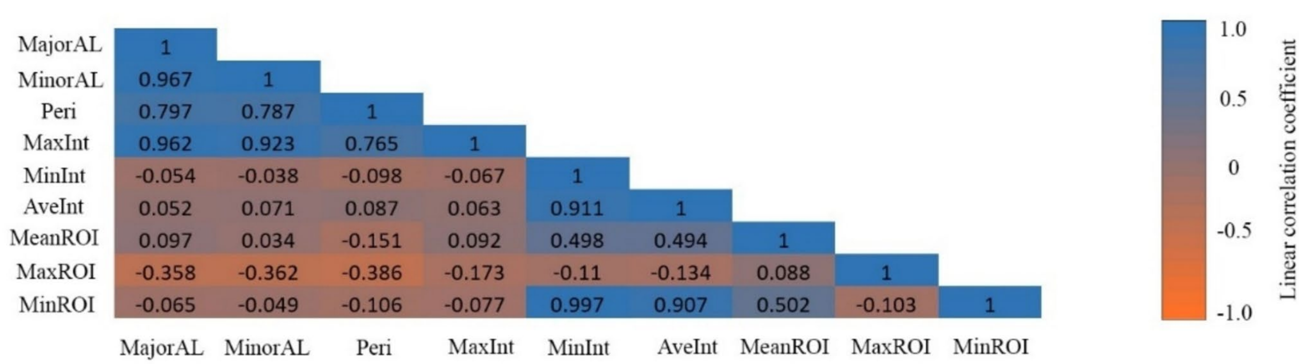


**Fig. 4** Linear correlation coefficients between all image parameters of *Terung Asam*

for identifying dynamic physiological processes during ripening.

MinInt exhibits negative correlations with the majority of variables, with the exception of AveInt, which has a correlation of 0.911, and MinROI, which shows a strong correlation of 0.997, highlighting its strong association with average and minimum intensities. These relationships imply that MinInt reflects more stable or cooler areas of the fruit surface, potentially indicating early moisture loss or internal cooling, and is useful for distinguishing between ripeness levels and early spoilage (Lee et al., 2025; Yogesh et al., 2021). MaxROI exhibits negative correlations with most variables, particularly with Peri which has a correlation of −0.386 signifying negative trends. This suggests that fruits with less perimeter complexity tend to exhibit higher localised peak temperatures, possibly due to concentrated heat spots. This finding is supported by Zeng et al. (2020), who demonstrated that thermal imaging's region-based temperature features effectively detect bruising in pears in where areas with more concentrated heat spots indicating internal damage and decay. Additionally, the correlation analysis revealed that MaxInt, MinInt, MajorAL and MajorAL were the most influential parameters for classifying *Terung Asam* across different storage days. These features, which integrate both thermal and geometric traits, significantly enhance the discrimination power of classification models by capturing physiological activity and morphological changes during ripening. The observed linear correlations among all thermal image parameters further support their effectiveness in distinguishing fruit samples based on storage duration.

The correlation of imaging metrics, including MaxInt, MinInt and MajorAL, can substantially improve the classification of *Terung Asam* at various storage days. Study has shown the efficacy of thermal imaging in fruit classification. This finding was consistent with Waluyo et al. (2023), where the relationship between thermal image parameters and banana fruit diameter at different ripeness stages showed the efficacy of thermal imaging in banana fruit classification. Likewise, Goh et al. (2025) examined approaches for assessing the freshness of fresh fruit bunches of palm oil by non-invasive imaging technologies, thereby reinforcing their utility in fruit classification. Similarly, the study on pineapple cultivars conducted by Mohd Ali et al. (2022) emphasised the role of infrared thermal imaging in accurately classifying fruit quality during various storage conditions. The thermal data and surface temperature distribution are essential for precise classification of ripeness phases, offering an invaluable tool for agricultural quality management.

## Comparison of Machine Learning Models

### Model Prediction of Terung Asam Fruit Classification by Confusion Matrices

As the outputs of the Fine Decision Tree and Medium Decision Tree classifiers are indistinguishable in terms of accuracy, precision, recall and confusion matrices, the results have been summarised in a unified table as tabulated in Table 3. Both the Fine Decision Tree and Medium Decision Tree models attained an overall accuracy of 86.7% across all storage categories. This value is consistent across the storage days in the table, as it represents the model's average performance rather than per-class accuracy. These classifiers demonstrated flawless performance in predicting fruits stored for 7 and 14 days, achieving 100% precision and recall. The models exhibited moderate efficacy in differentiating between fruits stored for 21 days and 28 days, achieving a recall of 66.7% for both categories, suggesting potential for enhancement in distinguishing extended storage durations. The models' tendency to misclassify fruits stored between 21 and 28 days may stem from similarities in data characteristics during these storage durations, requiring additional enhancement via feature engineering or data augmentation (M. M et al., 2024). These findings support similar challenges reported in other studies, where late-stage storage increases feature overlap, reducing model differentiation capability, and highlighting the importance of temporal-specific feature extraction (Shu et al., 2025).

The classification performance of *Terung Asam* at various storage days utilising RUSBoost Tree approach is tabulated in Table 4. RUS Boost Tree classifier obtained an overall accuracy of 85.9%. At 0, 7 and 14 days, the model attained flawless Recall achieving 100.0%, signifying that the classifier accurately recognised all samples for these timeframes.

**Table 3** Classification performance of *Terung Asam* at different storage durations using Fine and Medium Decision Tree models, where accuracy refers to the overall model performance across all classes

| Storage duration | True positive (TP) | True negative (TN) | False positive (FP) | False negative (FN) | Precision (PPV) | Recall (TPR) | Accuracy (%) |
|---|---|---|---|---|---|---|---|
| 0 | 27 | 90 | 0 | 6 | 81.8% | 100.0% | 86.7 |
| 7 | 27 | 90 | 0 | 0 | 100.0% | 100.0% | 86.7 |
| 14 | 27 | 90 | 0 | 0 | 100.0% | 100.0% | 86.7 |
| 21 | 18 | 99 | 4 | 7 | 72.0% | 66.7% | 86.7 |
| 28 | 18 | 99 | 2 | 5 | 78.3% | 66.7% | 86.7 |

**Table 4** Classification performance of *Terung Asam* at different storage durations using the RUSBoost Tree model, where accuracy values represent overall classification performance across all classes

| Storage duration | True positive (TP) | True negative (TN) | False positive (FP) | False negative (FN) | Precision (PPV) | Recall (TPR) | Accuracy (%) |
|---|---|---|---|---|---|---|---|
| 0 | 27 | 89 | 5 | 0 | 84.4% | 100.0% | 85.9 |
| 7 | 27 | 89 | 0 | 0 | 100.0% | 100.0% | 85.9 |
| 14 | 27 | 89 | 0 | 0 | 100.0% | 100.0% | 85.9 |
| 21 | 16 | 100 | 6 | 11 | 72.7% | 59.3% | 85.9 |
| 28 | 19 | 97 | 8 | 8 | 70.4% | 70.4% | 85.9 |

The Precision was very high, achieving 100% for both 7 and 14 days, while recording 84.4% for 0 days. Over a period of 21 days, the classifier's Precision decreased to 72.7%, while the Recall was 59.3%, signifying that the model encountered difficulties in accurately classifying samples during this time frame. This was also seen in the increased incidence of 11 false negatives and 6 false positives indicating some ambiguity between samples of 21 and 28 days. Over a duration of 28 days, the classifier had a balanced performance, achieving Precision and Recall rates of 70.4% each. Despite the model's successful classification of most samples for this storage time, the occurrence of 8 false positives and 8 false negatives suggest potential enhancements in differentiating 28 days samples from other groups. In the same manner, Chabalala et al. (2023) examined the effects of imbalanced data distributions on fruit-tree crop classification, emphasising that datasets with redundant or similar properties could reduce classifier efficacy. Their findings revealed that the classification accuracy of several machine learning classifiers diminished when there were imbalances or slight variations in data distributions between classes, which was expected to arise during the 21 to 28 days storage period of *Terung Asam* fruits.

The classification performance of *Terung Asam* at various storage days utilising Boosted Tree approach is tabulated in Table 5. The Boosted Tree classifier obtained an overall accuracy of 85.9%. At 0, 7 and 14 days, the model attained flawless Recall achieving 100.0%, indicating that all samples from these categories were accurately classified. The Precision reached its peak at 100.0% for both 7 and 14 days, but it was somewhat reduced to 87.1% for 0 days, attributed to a limited number of 4 false positives. Over a period of 21 days, the classifier's Recall decreased to 55.6%, indicating that over half of the samples from this duration were inaccurately classified as different storage periods, as evidenced by the elevated count of 12 false negatives. The Precision was 71.4%, indicating that although some predictions were accurate, there were still 6 false positives, resulting in a decline in performance for this area. Over a duration of 28 days, the classifier exhibited superior performance compared to the 21-day period, achieving a Recall of 74.1%, indicating that the majority of the 28 days samples were accurately classified. Nevertheless, the Precision was reduced to 69.0% owing to the occurrence of 9 false positives. The equilibrium between false positives and false negatives in this category indicates that the model encountered greater difficulty in differentiating between 28 days and other durations. Similarly, Riansyah et al. (2023) discovered that Boosted Trees attain maximum efficiency under conditions of clear class separability, but encounter difficulties in situations that involve increased feature overlap, suggesting further feature engineering to improve model stability. This correlates with the observations of Chabalala et al. (2023), who stated that classifier efficacy increased during the first storage period of *Terung Asam* on 0 to 14 days, where specific temperature features enabled precise classification.

The classification performance of *Terung Asam* at various storage days utilising Fine kNN classifier approach is tabulated in Table 6. The Fine kNN classifier achieved an overall accuracy of 84.4%. For 0 days, the Fine kNN classifier demonstrated a Precision of 87.1% and a Recall of 92.6%, indicating satisfactory performance in differentiating

**Table 5** Classification performance of *Terung Asam* at different storage durations using Boosted Tree, where accuracy refers to the overall model performance across all classes

| Storage duration | True positive (TP) | True negative (TN) | False positive (FP) | False negative (FN) | Precision (PPV) | Recall (TPR) | Accuracy (%) |
|---|---|---|---|---|---|---|---|
| 0 | 27 | 90 | 4 | 0 | 87.1% | 100.0% | 85.9 |
| 7 | 27 | 90 | 0 | 0 | 100.0% | 100.0% | 85.9 |
| 14 | 27 | 90 | 0 | 0 | 100.0% | 100.0% | 85.9 |
| 21 | 15 | 99 | 6 | 12 | 71.4% | 55.6% | 85.9 |
| 28 | 20 | 99 | 9 | 7 | 69.0% | 74.1% | 85.9 |

**Table 6** Classification performance of *Terung Asam* at different storage durations using Fine k-Nearest Neighbours (kNN), where accuracy refers to the overall model performance across all classes

| Storage duration | True positive (TP) | True negative (TN) | False positive (FP) | False negative (FN) | Precision (PPV) | Recall (TPR) | Accuracy (%) |
|---|---|---|---|---|---|---|---|
| 0 | 25 | 90 | 4 | 2 | 87.1% | 100.0% | 84.4 |
| 7 | 27 | 90 | 0 | 0 | 100.0% | 100.0% | 84.4 |
| 14 | 27 | 90 | 0 | 0 | 100.0% | 100.0% | 84.4 |
| 21 | 15 | 99 | 8 | 12 | 71.4% | 55.6% | 84.4 |
| 28 | 20 | 99 | 9 | 7 | 69.0% | 74.1% | 84.4 |

this category from others. The count of false negatives was 2, while there were 4 false positives. For both 7 days and 14 days, the classifier exhibited perfect performance, attaining Precision and Recall scores of 100%, signifying that all samples in these categories were accurately identified. For 21 days, the classifier exhibited a Recall of 55.6%, signifying that it overlooked a considerable percentage of samples within this category. There were 12 false negatives and 8 false positives, resulting in a precision of 71.4%. These misclassifications indicate the model's challenge in distinguishing 21-day data from various storage periods. Over a period of 28 days, the classifier shown modest efficacy, achieving a Precision of 69.0% and a Recall of 74.1%. This indicates that, although it accurately classified the majority of samples, it still produced 9 false positives and 7 false negatives, hence diminishing its classification quality for this category. The findings align with the study by Iwan Sudipa et al. (2024), which employed kNN for fruit quality assessment, highlighting comparable classification challenges as the fruit matures, frequently leading to reduced precision and recall rates. They also highlighted that such issues emerge as data features overlap more as storage time extends, especially for fruits exhibiting comparable visual traits at various stages. A related study by Zárate et al. (2023) emphasised that even lightweight models like kNN can show high accuracy when combined with rigorous k-fold cross-validation protocols, underscoring the critical importance of systematic validation before practical deployment.

To strengthen the model's real-world utility, future efforts should incorporate external validation datasets representing different environmental, seasonal and varietal conditions. Without this, model generalisation remains speculative. In practical terms, these results are promising for integrating early-stage classifiers into thermal-based sorting systems or automated post-harvest inspection lines. However, before deployment, model performance must be verified under uncontrolled conditions to confirm adaptability and reliability.

Figure 5 illustrates the confusion matrices for all prediction models, quantifying the observed misclassifications and providing extensive insights into their classification performance across storage periods.

### Model Prediction of Terung Asam Fruit Classification by Scatter Plot

The average classification accuracies of *Terung Asam* fruit at different storage days utilising five classifiers (Fine Decision Tree, Medium Decision Tree, RUSBoost Tree, Boosted Tree and Fine kNN) are presented in Table 7. The results illustrate the performance trends of the classifiers, offering significant insights into their relevance for the storage management of *Terung Asam* fruit. To build industrial confidence in these classifiers, external validation using unseen datasets from alternate post-harvest environments is critical.

On day 0, the classification accuracies were notably high across all models, with the Boosted Tree attaining the greatest accuracy of 87.1%, followed by Fine kNN at 86.2% and RUSBoost at 84.4%, while the remaining classifiers exhibited comparable performance at 81.8%. This corresponds with a previous study indicating that machine learning algorithms have successfully classified citrus fruit (Raza et al., 2025) and apple fruit (Chowdhury et al., 2024), utilising high-quality characteristics during the initial phases of degradation. This pattern is further demonstrated by the scatter plots for each classifier in Fig. 6. On day 0, all classifiers demonstrated a clear grouping of data points, signifying that the thermal characteristics of freshly harvested *Terung Asam* fruit were easily distinguished. The Boosted Tree and Fine kNN scatter plots indicated closely knit, distinctly separated clusters with minimal overlap, enhancing their classification efficacy. These results indicate that thermal and decision-tree-based classifiers could be deployed in real-time sorting stations directly after harvest, ensuring quality segmentation before storage or distribution.

Notably, on day 7 and day 14, all classifiers achieved 100% accuracy. This indicates that in the initial phases of storage, the classifiers could accurately differentiate the attributes of *Terung Asam*, presumably because of negligible degradation or modification in features throughout this timeframe. This corresponds with results from fruit classification research employing deep learning and transfer learning models, wherein optimal classification accuracy is frequently attained during optimal storage periods (Amin et al., 2023; Mukhiddinov et al., 2022). The scatter plots for these

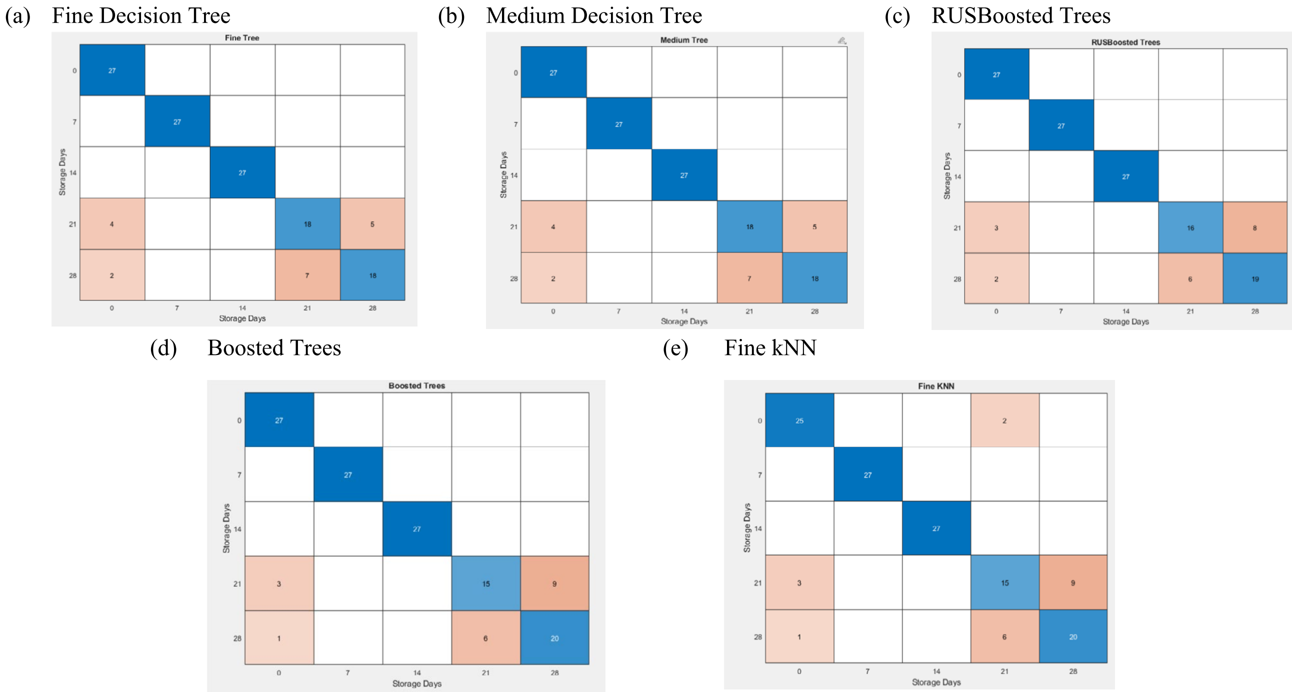


**Fig. 5** Confusion matrices for all prediction models: **a** Fine Decision Tree, **b** Medium Decision Tree, **c** RUSBoosted Trees, **d** Boosted Trees and **e** Fine kNN. Blue cells indicate correct classifications, while peach cells highlight misclassifications

**Table 7** Average classification accuracies of *Terung Asam* at different storage duration using various classifier algorithms

| Storage duration | Correct classification (%) | | | | |
|---|---|---|---|---|---|
| | Fine Decision Tree | Medium Decision Tree | RUSBoost Tree | Boosted Tree | Fine kNN |
| **Day 0** | 81.8 | 81.8 | 84.4 | 87.1 | 86.2 |
| **Day 7** | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| **Day 14** | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| **Day 21** | 72.0 | 72.0 | 72.7 | 71.4 | 65.2 |
| **Day 28** | 78.3 | 78.3 | 70.4 | 69.0 | 69.0 |
| **Overall accuracy rate (%)** | 86.7 | 86.7 | 85.9 | 85.9 | 84.4 |

days (Fig. 6a–e) exhibit compact, non-overlapping clusters for each classifier, indicating the models' proficiency in accurately classifying the fruits during these storage periods.

By day 21, classification accuracy decreased, especially for Fine kNN, which fell to 65.2%, but the other models exhibited relative stability, fluctuating between 71.4% and 72.7%. The loss in performance may be linked to heightened variability in the physical and chemical properties of *Terung Asam* over extended storage periods, potentially impacting model predictions. Chowdhury et al. (2024) identified the same issues in their study on apple quality detection, stating that prolonged storage resulted in significant changes in fruit properties, therefore complicating the classification process for machine learning models. The variation in physical qualities over storage periods decreased the accuracy of models like kNN, supporting the idea that alterations in fruit characteristics may affect model performance. The scatter plots illustrate this issue in which overlapping clusters are especially evident in the Fine kNN and RUSBoost Trees models (Fig. 6c, e), where the thermal characteristics of day 21 preserved fruits intersect with those of other storage durations. The overlap led to increased misclassifications, as evidenced by the models' confusion matrices. These reductions align with findings demonstrating the difficulties of accurate classification when products undergo metabolic alterations during prolonged storage durations (Gilani et al., 2022). As visual separability diminishes, especially in the presence of overlapping features, dynamic feature extraction or adaptive window-based sampling may help regain classification reliability.

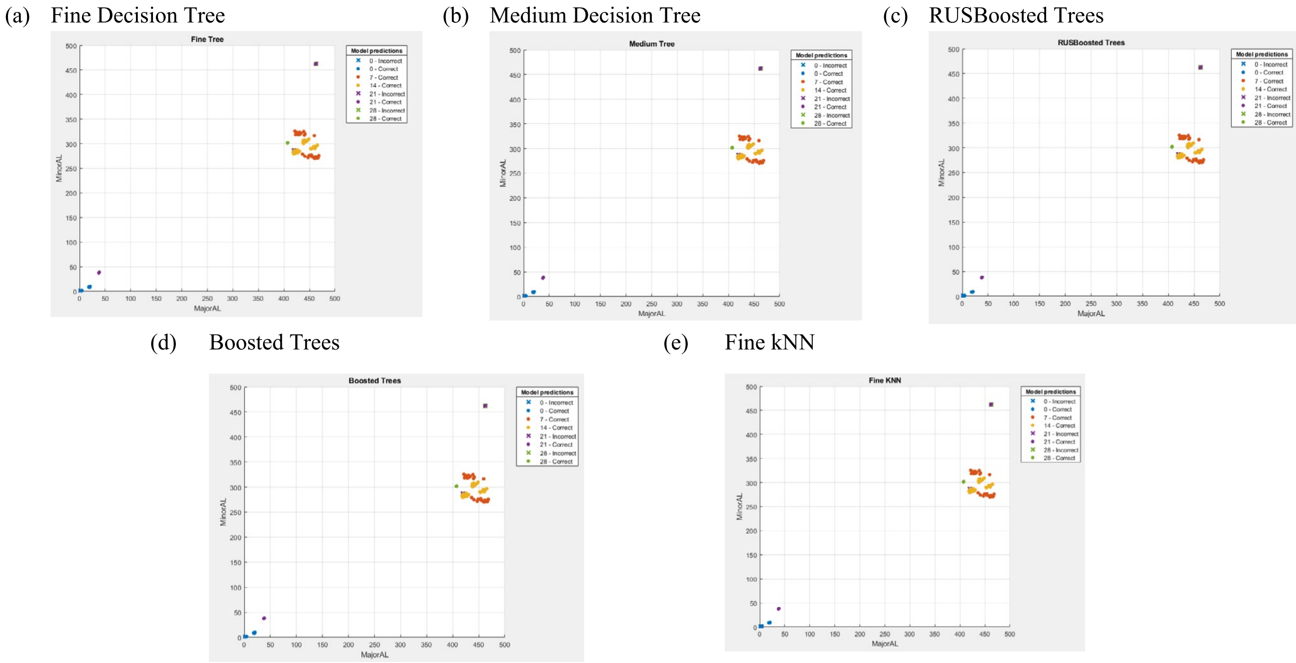


**Fig. 6** Scatter plots showing model predictions for *Terung Asam* classification using different machine learning algorithms, derived from the output visualisations generated in MATLAB (Version R2020a, The MathWorks, USA): **a** Fine Decision Tree, **b** Medium Decision Tree, **c** RUSBoost Trees, **d** Boosted Trees and **e** Fine k-Nearest Neighbor (kNN). Correct classifications are indicated by circular markers, while incorrect predictions are marked with crosses

That was a significant drop in a QC that was observed on day 28. This is especially true for RUSBoost Tree and Boosted Tree at 70.4% and 69.0%, respectively. However, the Fine and Medium Decision Trees recorded the highest accuracy at 78.3%. By observing the scatter plots for these classifiers (Fig. 6a, b), it was noted that a better separation was observed, which shows that the decision tree–based models were more accurate in identifying small differences in thermal feature in longer storage durations. The research by Sengar et al. (2023) found a similar pattern whereby it was shown that decision tree models happen to be more adept to collect small fluctuations in data over a long period of time. It is evident from their study that decision trees have greater classification in terms of accuracy as compared to other machine learning models when it comes to complex datasets with variable features. This highlights that decision tree–based methods, which includes the Fine and Medium Decision Trees, are more adaptable to varying data distribution over a long period of storage time. There is a lot of similarities between the day 21 and day 28 samples, based on the scatter plots RUSBoost and Boosted Trees (Fig. 6c, d). This shows that it is more difficult to identify the fruits' features accurately, and this has been evident in new research on classification of freshness using deep learning methods for perishable goods (Bhatt et al., 2019; Kang & Gwak 2022). This trend also reflects the challenge of maintaining classification robustness under fluctuating real-world conditions, as feature overlap increases. A recent study by Raza et al. (2025) addressed this issue by deploying a CNN-based citrus classification system using X-ray imaging, achieving 98% accuracy even under variable ambient storage and lighting conditions. Their work demonstrates the feasibility of translating machine learning classifiers into real-time post-harvest quality control systems despite feature drift and uncontrolled environments. Similarly, the visual clustering patterns observed in our scatter plots particularly in earlier storage days suggest that the Fine and Medium Decision Tree classifiers could serve as core components in automated fruit grading stations. However, to transition toward industrial implementation, model validation on external datasets collected under practical post-harvest conditions remains an essential future step.

The total classification accuracy indicates that Fine and Medium Decision Trees, both at 86.7%, somewhat surpassed the other models. This shows that tree-based models, specifically fine-grained decision trees, yield a more consistent outcome in the effort to manage various storage durations for agricultural classification tasks that align with latest advancement in decision tree algorithms for vegetable and fruit categorisation (Gilani et al., 2022). The outcome of this research shows that the methods of machine learning, specifically decision tree–based models, are effective in classifying *Terung Asam* at diverse storage duration. Nevertheless, a reducing trend in accuracy was observed as biochemical transformation of *Terung Asam* took place over a long period of time although decision tree models were observed to have a good performance during the early stages of classification. This outcome is in accordance with the research by Dasore et al. (2025) who found that storage time as well as changes in temperature affect the efficacy of machine learning models when they classify glutinous rice. This shows that temperature as well as the duration of storage significantly impact the machine learning models' performance and therefore necessitates more advanced optimisation methods like hyperparameter tuning to ascertain reliability in prediction. Likewise, in the classification of the *Terung Asam*, although Boosted Tree models and Fine Decision Tree models yield a good performance in controlled conditions, the performance deteriorates when the duration of storage was increased. This shows that more advanced methods in pre-processing are required to address the mismatches in classification. Integrating many advanced technologies would help in addressing these limitations. For example, machine learning with thermal imaging provides a non-invasive technique to classify fruits across various durations of storage. The adjustment in model parameters and integration of additional feature extraction methods were proposed by Dasore et al. (2025). This is believed to enhance classification performance under various diverse storage settings. When implementing these methods, post-harvest monitoring becomes easier, and classification errors can be reduced. Furthermore, agricultural machine learning applications can be optimised by ensuring the enhanced responsiveness to changes of biochemical in stored product.

## Conclusion

This study demonstrated that thermal imaging parameters of *Terung Asam* fruit can efficiently monitor ripening and senescence throughout storage periods. Among the nine parameters examined, MajorAL, MaxInt and MinInt exhibited the most significant changes indicating crucial physiological changes. Correlation analysis demonstrated strong positive correlation between MajorAL and MinorAL ($r = 0.967$) and between MajorAL and MaxInt ($r = 0.962$), highlighting their combined effectiveness in ripeness detection. Of the five models, Fine and Medium Decision Trees achieved the highest accuracy at 86.7%, revealing that thermal imaging data can effectively provide non-destructive, automated assessment of the maturation of fruits. The integration of thermal imaging and machine learning enables the monitoring of internal and surface physiological changes that conventional imaging fails to detect, offering practical data for post-harvest management. Such findings can help optimise storage conditions, enhance quality control and minimise waste. Future studies must validate these findings using independent datasets, conduct RGB-thermal image comparison, investigate advanced or hybrid modelling techniques to address feature overlap in subsequent storage phases and evaluate scalability across various cultivars and environmental conditions to guarantee wider applicability in practical agricultural applications.

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**Data Availability** All data generated or analysed in this research are presented within this published article.

## Declarations

**Competing interests** The authors declare no competing interests.



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