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Quality prediction of different pineapple (*Ananas comosus*) varieties during storage using infrared thermal imaging technique

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ABSTRACT

Infrared thermal imaging is a powerful tool used to monitor the quality and safety of various agricultural products. In this study, infrared thermal imaging was used to evaluate the quality of pineapples during storage. Freshly harvested pineapples of different varieties were stored at 5 °C, 10 °C, and 25 °C for 21 days with 360 samples at each storage temperature. The thermal images were segmented to obtain feature selection based on image parameters. The physicochemical properties of pineapples including firmness, pH, total soluble solids, moisture content, and colour measurements for different varieties were also determined using standard reference methods. Significant differences were found between image parameters and the physicochemical properties of pineapples as well as in the interaction between the applied storage treatments. The prediction performance of pineapple quality was developed using partial least squares regression which obtained R^2 values up to 0.94 for all the quality parameters of the pineapple varieties. The results revealed that 10 °C was found to be the most ideal storage temperature for all the physicochemical properties of the fruit. The variation in the image parameters in relation to the different varieties and storage temperatures were successfully discriminated with overall classification accuracies higher than 97% using support vector machines. Therefore, infrared thermal imaging is feasible as a non-destructive tool for monitoring the fruit quality which could enhance the operation and postharvest handling of pineapples under different storage conditions.

1. Introduction

Pineapple quality plays a major factor in determining the market price and consumer preference. In 2019, Costa Rica was ranked first for the top pineapple producing country worldwide followed by the Philippines and Brazil (FAOSTAT, 2021). Pineapple has different chemical content according to different varieties as well as ripening stages of the fruit (Montero-Calderón et al., 2020). Currently, there are more than 100 pineapple varieties present wherein only 6 to 8 varieties are cultivated commercially (Mohd Ali et al., 2020). Generally, visual inspection such as firmness, bruising, external defects, and colour changes are regarded as the key criteria for the customers to assess the quality of the fruit (Dittakan et al., 2018). The main problem arises during the postharvest handling of pineapple in which the defects start to appear until several days after the fruit has been exported (Siti Rashima et al., 2019). This is one of the main issues in the pineapple industry since the fruit quality cannot be determined at an early stage by visual appearance during postharvest handling which can influence the choice and palatability of the consumers. In this case, the evaluation of pineapple quality is essential in order to ensure only good-quality fruits are distributed to the commercial chain.

Pineapple is a tropical and non-climacteric fruit that does not ripen after harvest. Non-climacteric fruits produce low ethylene which does not demonstrate major changes in the respiration process during ripening (Ikram et al., 2020). Pineapple fruit is highly perishable that could lead to significant postharvest losses. For instance, several causes of pineapple quality are associated with postharvest losses including mechanical injuries, cracks, cutting injuries, rot, and skin defects (Pulissery et al., 2020). The quality evaluation of pineapples remains a challenge in scientific studies for exploring precise and accurate

Abbreviations: TSS, total soluble solids; PLS, partial least squares; SVM, support vector machine.

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detection methods. Several criteria which could influence the quality attributes of pineapples need to be addressed such as varieties, ripening stages, storage temperature as well as the geographical origin of the fruit (Padrón-Mederos et al., 2020). Nevertheless, the changes in pineapple attributes may easily cause quality deterioration and the undesirable losses are normally accumulated because of the destructive nature of the conventional analysis (Adiani et al., 2020; Priyadarshani et al., 2019). For this reason, advanced and non-destructive techniques specifically for pineapples are required which could determine the fruit quality without damaging the whole fruit.

The potential of non-destructive techniques as a sensing tool for the quality and safety evaluation of fruit has been reported in various studies. To address the concern related to fruit quality, the infrared thermal imaging technique has been considered due to its ability of non-contact and being less-labour intensive for various agricultural produce (Mangus et al., 2016). The advantages of infrared thermal imaging are high repeatability, easy operation, and fast detection speed, making it a powerful tool for monitoring the quality attributes of foods and agricultural products (Ishimwe et al., 2014; Roslidar et al., 2020). In recent years, infrared thermal imaging has been developed to detect quality and safety inspection of different types of fruit such as apple (Chandel et al., 2018), grape (Ding et al., 2017), mango (Naik & Patel, 2017), and guava (Gonçalves et al., 2016). However, the available applications involving infrared thermal imaging on food products at an industrial scale are still limited. Senni et al. (2014) reported the application of infrared thermal imaging to detect foreign bodies in biscuits using temporal sequences of thermograms gathered at the exit of the oven during the cooling process. Chandel et al. (2018) evaluated the surface temperature estimation of apples using thermal imaging coupled with micro-climate sensor data, and an open-field weather station. Zeng et al. (2020) evaluated the thermal images of different types of bruises of pear coupled with hot air treatment using high velocity and air temperature. In research work performed by Mohd Ali et al. (2021), it was reported that the thermal images were used to extract image features for discrimination of different ripening stages of durian. Kuzy et al. (2018) used a thermographic imaging system based on the feature extraction of healthy and bruised thermal images of blueberries which yielded a classification rate of 90%. Hence, this study aims to evaluate the feasibility of infrared thermal imaging in monitoring the quality attributes of pineapples during storage by (1) determining the quality changes of pineapple varieties under different storage conditions, (2) developing prediction models based on image parameters, and (3) establishing classification results of the variations in physicochemical properties of pineapple varieties.

2. Material and methods

2.1. Sample preparation

The investigation was carried out on three different pineapple varieties i.e. MD2, Josapine, and Morris. These varieties were chosen as they are the most marketable and exported in Malaysia (Safari et al., 2019). A total of 1080 fresh pineapples at a ripening stage of Index 2 were used in this study. At this ripening stage, the fruit were 50% unripe with glossy dark green and traces of yellow in colour between eyes at the base. The fruit were harvested from a local farm in Simpang Renggam, Johor, Malaysia and transported to the laboratory at the Faculty of Engineering, Universiti Putra Malaysia. The samples were stored at three different storage temperatures i.e. in a cold storage room (5 °C), a controlled refrigerator (10 °C), and an air-ventilated laboratory room (25 °C) with a temperature range of ±2 °C and relative humidity of 85–90%. The samples were randomly numbered and labelled accordingly for identification purposes.

For each variety, 30 samples were randomly selected for data collection at every seven days interval (Day 0, Day 7, Day 14, and Day 21). The samples were subjected to infrared thermal imaging analysis and quality reference measurements. The images of different varieties of pineapples at different storage days (Day 0, Day 7, Day 14, and Day 21) stored at 5, 10, and 25 °C are shown in Figs. S1–S3. The image acquisition of the fruits was performed immediately upon removing the samples from the storage. The same fruit samples were also used for both image acquisition and quality reference measurement. The fruits were kept in a laboratory room for 2 h before the experiments were conducted to ensure the equivalent of the temperatures within the samples and surroundings.

2.2. Infrared thermal imaging acquisition

The infrared thermal imaging system consisted of a sample holder, a thermographic camera (FLIR E60, FLIR systems, King Hills, United Kingdom), and a computer for image storage that was developed for the data acquisition process. The camera device was equipped with an infrared range of 0.7–1.4 μm and a temperature control ranging from −20 °C to +650 °C. The camera lens had a thermal sensitivity of less than 0.05 °C and a field of view of 25° × 19° was used to capture the thermal images. The distance between the camera device and the sample was fixed at 40 cm. The thermal images were acquired at a room temperature of 25 °C with an infrared resolution of 320 × 240 pixels. A total of 3240 thermal images were obtained for the overall pineapple samples. The thermal images of three different pineapple varieties at different storage temperatures are as shown in Fig. 1.

2.3. Reference quality measurements

The physicochemical properties of all samples were measured including firmness, total soluble solids (TSS), pH, moisture content, and colour evaluation. The firmness of the pineapple was measured using a GY-1 electronic penetrometer (G-tech Co. Ltd., China) fitted with a 3.5 mm diameter plunger tip. Three readings were measured on each section of the fruit (top, middle, and bottom) and expressed in N. The TSS values were measured using a digital refractometer (Pal-1, Atago Co., Japan) at the top, middle, and bottom sections. The mean values of these measurements were calculated and expressed as %. The pH of the pineapple juice was determined using a pH meter (DPH-2, Atago Co., Japan) and

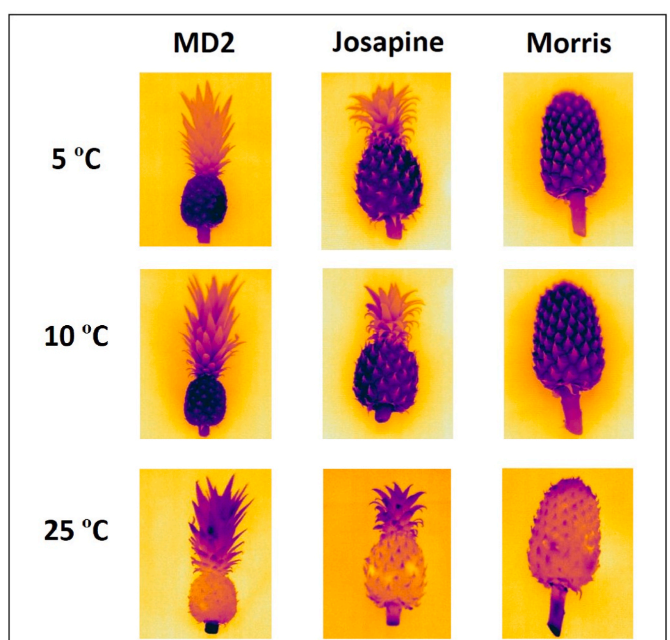

Fig. 1. The thermal images of three different varieties of pineapples at different storage temperatures.

expressed as units of pH. The moisture content was measured using an oven drying method at 105 °C until a constant weight was reached. The measurements were expressed as the percentage based on a wet basis. The surface colour of pineapple flesh was evaluated using a colorimeter (NR20XE, Shenzhen 3nh Technology, China) with a 20 mm measuring aperture. The mean values at three different sections were calculated.

2.4. Thermal image processing and analysis

The acquired thermal images were analysed based on the extracted morphological features that were then correlated to the changes in physicochemical properties of the fruit during storage. As reported by Prasad et al. (2017), the morphological features can be identified from thermal image analysis based on the thermal differences of the fruit sample and further used for chemometric analyses. The morphological features are tailored based on the chemical composition of the fruit that was performed at the initial step of image processing and analysis (Koklu & Ozkan, 2020). Chemical composition is used as basic intrinsic properties which carry relevant information on the morphological attributes of the fruit. In this case, morphological features were selected to describe the quality of pineapples according to the physicochemical properties of the sample. Particularly, the pixel value and shape features from thermal images were obtained in order to eliminate the high dimensionality of the acquired data. These features were extracted by means of image processing and analysis due to the high influence of morphological features in evaluating the performance of the prediction and classification tasks (Jamil & Bejo, 2014; Jawale & Deshmukh, 2017; Johari et al., 2021; Mohd Ali et al., 2021). In addition, pixel value and shape features of pineapple varieties have no external discriminatory features that are vital for assuring fruit quality. Most methods for the detection of fruit quality have utilised feature extraction such as shape and pixel value in which the region of interest of the obtained image is distinguishable.

Before performing feature extraction, the acquired images were pre-processed and segmented. The pre-processing and image segmentation steps of the thermal images are shown in Fig. 2. The image processing and segmentation steps comprise the removal of background and the selection of the region of interest. The thermal image was converted to grayscale image for the feature extraction method. The histogram information based on the grayscale image was obtained by calculating the optimal threshold value. The thresholding technique was applied to select the threshold value in order to convert the grayscale image into a binary image. The region of interest was segmented from the image according to the threshold value. Several features were extracted after the image segmentation step based on the pixel value and shape features. In total, eight shapes (centroid, area, eccentricity, perimeter, orientation, major axis length, minor axis length, and extent) and six pixel values (maximum intensity, mean intensity, minimum intensity, maximum of region of interest, mean of region of interest, and minimum of region of interest) features were obtained for each pineapple image. The feature extraction was obtained using MATLAB Version R2020a software (The MathWorks, USA). All the selected features were derived as image parameters in the pixel count values.

2.5. Data analysis

Basic descriptive statistical details and significant differences of the physicochemical properties of pineapple varieties under different storage conditions were obtained using a two-way analysis of variance (ANOVA). The mean difference between the physicochemical properties and all storage treatments was analysed by conducting Tukey's test using the Unscrambler X Version 10.3 (CAMO Software, Oslo, Norway). The results were evaluated at a significance level of $P < 0.05$.

Partial least squares (PLS) regression was developed for the correlation between the image parameters as independent variables and

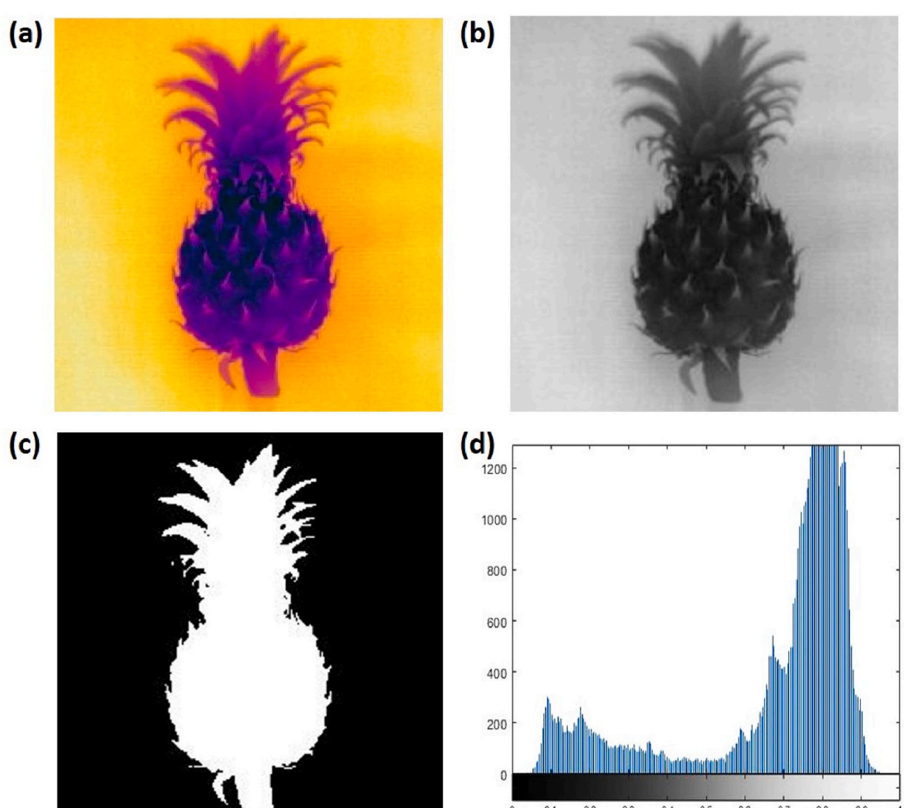

Fig. 2. The image processing and segmentation processes; (a) thermal image, (b) grayscale image, (c) region of interest of segmented image, and (d) histogram of grayscale image.

quality attributes of the fruit. The PLS analysis was carried out using the Unscrambler X Version 10.3 (CAMO Software, Oslo, Norway). The data were randomly split into calibration (70%) and prediction (30%) sets, respectively. The models were developed using calibration datasets containing 756 image datasets by regressing image features data as predictor variables and the actual value of physicochemical properties data as response variables. Ten-fold cross validation was used during the calibration to evaluate the predictive performance of the models. The optimal number of latent variable (LV) was determined according to the lowest prediction error in cross-validation. The most accurate model was chosen by the validation performance using prediction datasets containing 324 image datasets. The performance of the PLS models was determined based on several statistical indicators such as LV, root mean square error (RMSE), coefficient of determination (R^2), bias, ratio of performance to deviation (RPD), and ratio of error range (RER) between the measured and predicted quality attributes of pineapples.

Moreover, the support vector machine (SVM) was applied to the datasets to determine the quality attributes with classification performance according to the respective pineapple varieties. The dataset was randomly separated into a training dataset (70%) and a testing dataset (30%) for model validation in order to generate the SVM model. The training performance was evaluated using k-repeated fold cross-validation with a total number of 10 repetitions and k-value of 5 to select the optimal image parameters.

3. Results and discussion

3.1. Analysis of physicochemical properties

The changes in physicochemical properties including TSS, pH, firmness, and moisture content of pineapple varieties under different storage conditions are shown in Fig. 3. Based on the results, it was revealed that firmness was found to gradually decrease over the storage days of the fruit for all storage temperatures. A significant difference in firmness was observed from Day 0 until Day 21. The mean values of firmness for all pineapple varieties (MD2, Morris, and Josapine) were obtained at a range of 0.33–2.92 N. The textural firmness of different pineapple varieties gradually decreased which signified the maximum force upon penetration into the flesh as the storage days increased. Among all pineapple varieties, Josapine demonstrated the least variation in textural properties indicating longer shelf life compared to MD2 and Morris. Nguyen (2020) reported that the ripening of pineapple is caused by a breakdown of pectin and starch hydrolysis which could result in gradual textural softening. The rapid decrease in fruit firmness showed the correlation of the textural changes at different stages of maturity during the ripening process of the fruit (Li et al., 2018). These findings are in agreement with the research work performed by Leneveu-jenvrin et al. (2020) who exhibited a gradual decline in the firmness of pineapples during storage.

In a similar way, pH values also gradually decreased significantly ($P < 0.05$) from Day 0 until Day 21 for all pineapple varieties (MD2, Morris, and Josapine). Significant reductions in pH were found at a range of 2.40–4.10. For the MD2 variety, the fruit stored at 5 °C indicated the lowest pH values of 2.40 at Day 14. Meanwhile, the fruit samples stored at 25 °C recorded the highest pH values on Day 0. It was evident that as the storage temperature increased, a relatively low pH value could be expected. A similar study was reported for the measurement of pH values ranging from 3.9 to 5.0 for pineapple fruit (Ancos et al., 2016). The finding revealed that the ripe stage had the highest pH, indicating that the pineapple maturity was governed by the decrease in dominant citric acid during fruit ripening (Nadzirah et al., 2013). Notably, the results showed that the fruit stored at 5 °C and 25 °C gave a relative decrease in pH values of the pineapples compared to the fruit stored at 10 °C. Furthermore, the decrease in pH values of all pineapple varieties with respect to the temperature during storage was conducted in order to evaluate the shelf life and acceptability of the fruit (Chaudhary et al., 2019).

From the findings, the moisture content values of pineapples from

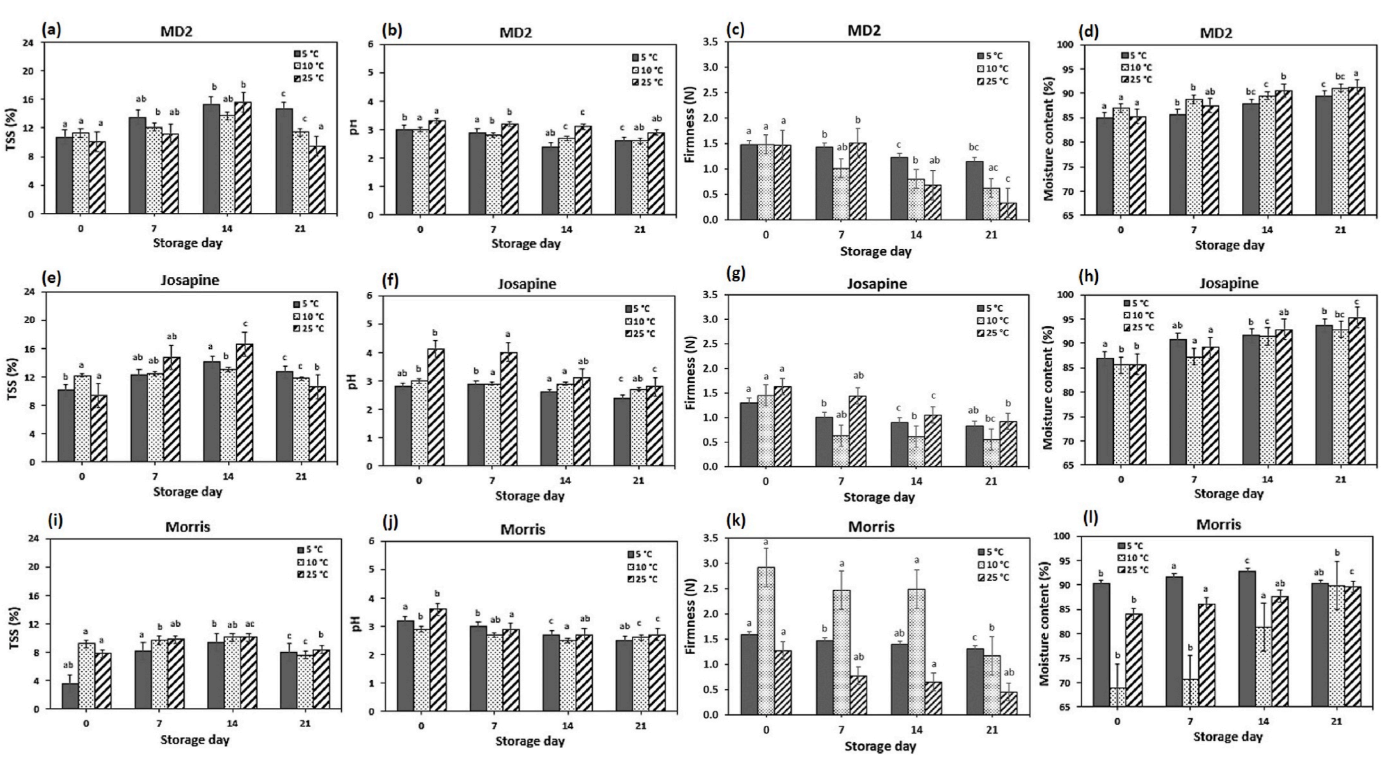

Fig. 3. Mean values and differences of (a) TSS for MD2, (b) pH for MD2, (c) firmness for MD2, (d) moisture content for MD2, (e) TSS for Josapine, (f) pH for Josapine, (g) firmness for Josapine, (h) moisture content for Josapine, (i) TSS for Morris, (j) pH for Morris, (k) firmness for Morris, and (l) moisture content for Morris at different storage temperature.

Day 0 to Day 21 ranged from 68.87 to 95.26% for all pineapple varieties (MD2, Morris, and Josapine). The Josapine and MD2 varieties recorded a rapid rise of moisture content values for fruit stored at 25 °C. In contrast, storage temperatures at 5 °C and 10 °C recorded the highest moisture content values of 93.66% and 92.86% from the Josapine variety, respectively. In this case, the empirical increase in the moisture content of the pineapples especially for the fruit samples stored at refrigerated temperatures occurred because of the high water loss process during storage. As the ripening stages of pineapples increased, it was noted that the moisture content also increased significantly ($P < 0.05$) for all the fruit varieties of MD2, Morris, and Josapine. A similar finding was found by Padrón-Mederos et al. (2020) who obtained moisture content values in pineapples ranging from 84 to 87% throughout the storage period. Nevertheless, the fruit stored at 25 °C within 21 days demonstrated a low reduction of moisture content (2–3%) compared to the fruit stored at 5 °C and 10 °C. This could imply that the fruit has low moisture content due to the degradation of water content during storage (Ismail et al., 2018).

On the other hand, the Josapine variety had the highest TSS values compared to MD2 and Morris for all storage conditions of the fruit. In this sense, the results indicated that the Josapine variety possessed a sweet taste at an early phase of the ripening process. In addition, it was observed that the TSS values of pineapples increased significantly ($P < 0.05$) along with the increase of storage days for all the fruit varieties. The high TSS in pineapples may be attributed to the conversion of starch to sugars including glucose, fructose, and sucrose during the fruit ripening (Siti Rashima et al., 2019). The pineapple samples stored at 25 °C gave the highest TSS values (16.60%) followed by 5 °C (14.60%), and 10 °C (13.70%), respectively. Based on the findings, it can be noted that as the storage temperature decreased, a relatively high TSS value was recorded for all the pineapple varieties. Furthermore, these observations were comparable to the studies of Dolhaji et al. (2019) who investigated the minimum TSS values of 12% which would be acceptable for the customer preferences for pineapple fruit.

The colour changes of pineapples in terms of L*, a*, and b* values increased significantly ($P < 0.05$) for all pineapple varieties with the increase of storage days of the fruit (Fig. 4). The L*, a*, and b* values were revealed to have been reduced by the different storage conditions. Based on the results, the L* values of the pineapples decreased from Day 0 until Day 21 ranging from 16.21 to 58.39 for all fruit varieties. The decrease in L* colour parameter in the pineapples was due to the reduction of acid content which lead to high intensity of lightness in the fruit tissue (Ancos et al., 2016). For the a* colour parameter, the Josapine variety recorded the highest values of 14.37 at Day 21 stored in 10 °C. Apart from that, a rising trend of b* values of the pineapples was achieved throughout all storage conditions for MD2, Morris, and Josapine from Day 0 to Day 21 in which the 25 °C was recorded as the highest (24.54). In this case, it was observed that the colour changes of pineapples with respect to L*, a*, and b* colour values were highly influenced by the different storage conditions ($P < 0.05$). In order to describe the colour changes in pineapples, Pulissery et al. (2020) discussed that the chemical reaction in the fruit tissue initiated by the microorganism and enzyme inactivation may cause the difference in terms of colour variation of the fruit during storage. From this observation, all the colour parameters of pineapples increased due to the progressed storage days in which the fruit turned to less green and steadily became more yellowish.

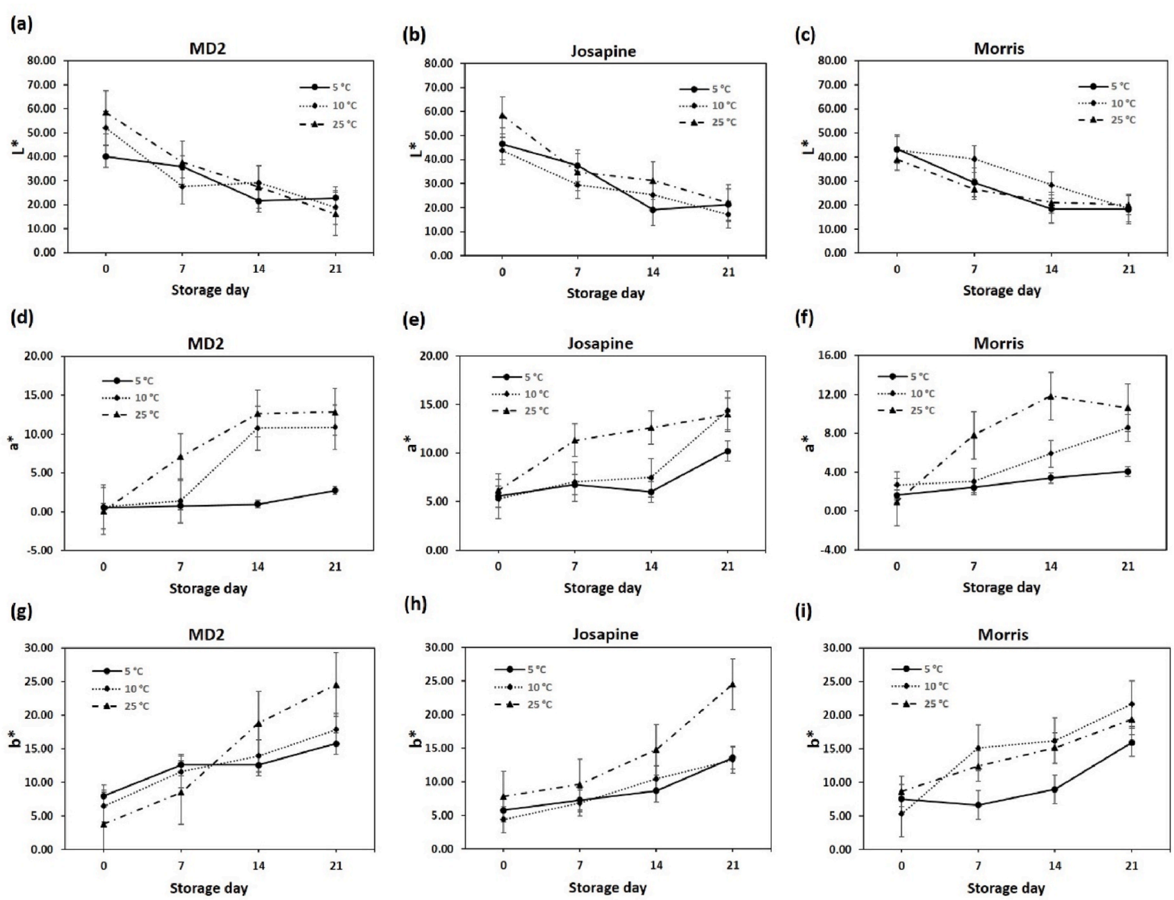

Fig. 4. Colour changes of (a) L* for MD2, (b) L* for Josapine, (c) L* for Morris, (d) a* for MD2, (e) a* for Josapine, (f) a* for Morris, (g) b* for MD2, (h) b* for Josapine, and (i) b* for Morris at different storage temperatures.

Table 1
Analysis of variance of image parameters in relation to storage temperature and variety.

Factor	Image parameter	Mean Square	F-value	Pr (>F)
Temperature	Centroid	138.93	2.00	0.036*
	Area	234428613.00	3.38	0.034*
	Eccentricity	0.03	15.33	<0.0001*
	Perimeter	12108859.00	3.20	0.041*
	Orientation	126.40	0.27	0.767
	Major axis length	282.90	0.38	0.007*
	Minor axis length	1623.00	1.56	0.011*
	Extent	0.01	2.37	0.004*
	Maximum intensity	0.23	109.66	<0.0001*
	Mean intensity	0.05	1.33	0.266
	Minimum intensity	0.14	94.82	<0.0001*
	Maximum of region of interest	0.0042	29.87	<0.0001*
	Mean of region of interest	0.53	238.61	<0.0001*
	Minimum of region of interest	0.14	43.32	<0.0001*
Variety	Centroid	4934.53	70.99	<0.0001*
	Area	4947983183.00	71.38	<0.0001*
	Eccentricity	0.26	153.82	<0.0001*
	Perimeter	6071655.00	1.61	0.201
	Orientation	1953.50	4.10	0.017*
	Major axis length	43706.70	58.04	<0.0001*
	Minor axis length	109820.00	105.44	<0.0001*
	Extent	0.04	12.07	<0.0001*
	Maximum intensity	0.02	11.94	<0.0001*
	Mean intensity	0.25	6.64	0.001*
	Minimum intensity	0.0020	1.36	0.257
	Maximum of region of interest	0.00041	2.89	0.056*
	Mean of region of interest	0.14	61.84	<0.0001*
	Minimum of region of interest	0.01	3.69	0.025*
Temperature*Variety	Centroid	448.52	6.45	<0.0001*
	Area	215821678.00	3.11	0.015*
	Eccentricity	0.0027	1.61	0.009*
	Perimeter	1832683.00	0.48	0.747
	Orientation	217.40	0.46	0.768
	Major axis length	8142.80	10.81	<0.0001*
	Minor axis length	5506.00	5.29	<0.0001*
	Extent	0.02	6.05	<0.0001*
	Maximum intensity	0.0045	2.18	0.009*
	Mean intensity	0.01	0.35	0.842
	Minimum intensity	0.11	75.69	<0.0001*
	Maximum of region of interest	0.00060	4.22	0.002*
	Mean of region of interest	0.03	13.96	<0.0001*
	Minimum of region of interest	0.09	29.31	<0.0001*

* Significant at $P < 0.05$.

3.2. Changes of image parameters during storage

Specific features were extracted from the thermal images based on the shape and pixel value features. The selected features were applied as inputs to the training models as well as employed as the prediction of physicochemical properties of different pineapple varieties during storage. The changes of image parameters showed the pixel distribution based on the temperature mapping attained at the surface of the pineapples for different varieties. Different combinations of those features were developed to evaluate the classification performance according to the storage conditions of the fruit. This scenario corresponded with the measurement of physicochemical properties of the fruit with the infrared properties of the wavelength region (Jimenez-Jimenez et al., 2012). Based on the results, the changes in thermal images of pineapples in all storage conditions signified a similar distribution of temperature mapping. It can be seen that the apparent variations were observed with consistent pixel intensities for all factors (day, temperature, and variety) in the pineapple fruit.

Table 1 shows the ANOVA results for the effect of storage temperature, variety, and the interaction between those factors based on the image parameters of the pineapples. Considering the interaction between these factors, it can be noted that almost all of the image parameters gave significant results in monitoring pineapple varieties during storage. Sanchez et al. (2020) discussed the interaction between several treatments and denoted a dependable reliability index of the overall experiment which could be useful in decision making concerning the suitability of the specific treatment used. The significant effect of storage temperature and variety signifies that the variation in temperatures has affected the changes of physicochemical properties of pineapples. For this reason, the temperature differences are associated with the effect of thermal diffusion as it passed through the surface of the samples (Farokhzad et al., 2020). Hence, the temperature difference between the pineapple varieties is varied considering a wide range of storage conditions as well as fruit maturation.

The effect of variety, storage day, and the interaction between these factors subjected to image parameters of pineapples is described in Table 2. For the interaction between these factors, it was observed that almost all of the image parameters were significantly influenced by different factors during storage. The significant interaction between the treatments revealed a good indicator for determining the reliability of the particular condition used which was influenced by its factor and their interaction (Khatiwada et al., 2016). It was revealed that the thermal images with a storage temperature of 10 °C demonstrated the most significant differences according to different pineapple varieties. All of the image parameters for each storage day were normalised to achieve a reasonable contrast ability. These image parameters were feasible to describe the behaviour of the thermal images of the pineapples, resulting in the high dependency based on different storage treatments.

Table 2
Analysis of variance of image parameters in relation to storage day and variety.

Factor	Image parameter	Mean Square	F-value	Pr (>F)
Day	Centroid	2431.56	45.83	<0.0001*
	Area	4760357696.00	104.22	<0.0001*
	Eccentricity	0.17	182.57	<0.0001*
	Perimeter	4836689.00	1.28	0.280
	Orientation	1478.50	3.20	0.023*
	Major axis length	17669.80	31.25	<0.0001*
	Minor axis length	55693.00	81.41	<0.0001*
	Extent	0.10	40.00	<0.0001*
	Maximum intensity	0.07	29.29	<0.0001*
	Mean intensity	0.12	3.12	0.025*
	Minimum intensity	0.02	9.74	<0.0001*
	Maximum of region of interest	0.0014	9.37	<0.0001*
	Mean of region of interest	0.06	19.16	<0.0001*
	Minimum of region of interest	0.01	2.28	0.078
Variety	Centroid	4934.53	93.01	<0.0001*
	Area	4947983183.00	108.32	<0.0001*
	Eccentricity	0.26	272.25	<0.0001*
	Perimeter	6071655.00	1.61	0.201
	Orientation	1953.50	4.23	0.015*
	Major axis length	43706.70	77.30	<0.0001*
	Minor axis length	109820.00	160.54	<0.0001*
	Extent	0.04	14.63	<0.0001*
	Maximum intensity	0.02	10.90	<0.0001*
	Mean intensity	0.25	6.70	0.001*
	Minimum intensity	0.0020	0.96	0.382
	Maximum of region of interest	0.00041	2.78	0.062
	Mean of region of interest	0.14	44.44	<0.0001*
	Minimum of region of interest	0.01	3.14	0.044*
Day*Variety	Centroid	2093.55	39.46	<0.0001*
	Area	2084854509.00	45.64	<0.0001*
	Eccentricity	0.05	57.59	<0.0001*
	Perimeter	5631331.00	1.49	0.178
	Orientation	2391.40	5.18	<0.0001*
	Major axis length	30465.30	53.88	<0.0001*
	Minor axis length	40512.00	59.22	<0.0001*
	Extent	0.06	24.15	<0.0001*
	Maximum intensity	0.01	5.08	<0.0001*
	Mean intensity	0.05	1.26	0.002*
	Minimum intensity	0.0036	1.70	0.118
	Maximum of region of interest	0.00020	1.36	0.226
	Mean of region of interest	0.01	4.56	<0.0001*
	Minimum of region of interest	0.01	2.10	0.051*

* Significant at $P < 0.05$.

3.3. Prediction performance of pineapple quality

To evaluate the performance of the quality prediction of different pineapple varieties, the PLS models were developed using feature extraction from the thermal images. The calibration and prediction models based on image parameters of different pineapple varieties are tabulated in Table 3. The infrared thermal imaging demonstrated good performance and predictive ability for all physicochemical properties of the pineapple varieties. The pH from the MD2 variety obtained the highest R^2 value of 0.91 with RMSEC of 0.10 for the calibration model among all the physicochemical properties of the pineapple varieties. The highest predictive ability in determining the TSS prediction of pineapples was found from the MD2 variety with an R^2 of 0.83 and RMSEP of 1.74 based on the PLS prediction model. Comparing the results with other pineapple varieties, the TSS prediction models obtained the highest R^2 values of 0.85 for the Hybrid N36 variety (Chia et al., 2012). Likewise, the pH prediction of pineapples also showed the highest values from the MD2 variety (R^2 = 0.94, RMSEP = 0.09) based on the prediction models. To develop a real-time infrared thermal imaging system for the detection of pineapple quality, the accuracy of the image parameter analysis as a non-destructive evaluation was highly dependent on the reliability of the reference data.

On the other hand, the relationship between the textural properties and image parameters of pineapples was signified by assessing the firmness of the fruit. The promising results obtained the highest predictive of firmness values from Morris variety (R^2 = 0.91, RMSEP = 0.04) compared to MD2 (R^2 = 0.87, RMSEP = 0.04) and Josapine (R^2 = 0.89, RMSEP = 0.05), respectively. For moisture content of pineapples, the best prediction ability was found for the calibration models from MD2 variety with R^2 of 0.87 and RMSEC of 0.59. Similarly, the prediction models for moisture content achieved the highest R^2 of 0.92 and RMSEP of 0.47 from the MD2 variety. The moisture content and firmness of pineapples were the common internal quality attributes that were used to evaluate the fruit maturity using optical detection approaches (Ramallo & Mascheroni, 2012). Furthermore, the prediction models for all physicochemical properties had RPD greater than 3 and RER greater than 12, which signified a good performance of the models. In brief, the combination of various image parameters with the reference measurements could be a contributing factor in the prediction results of quality attributes of the fruit (Doosti-Irani et al., 2016; Hahn et al., 2016).

In the case of colour evaluation of pineapple varieties, the PLS models obtained the R^2 values higher than 0.66 for L*, a*, and b* parameters. The best L* prediction model from MD2 variety yielded the highest prediction (R^2 = 0.89, RMSEC = 3.48) and (R^2 = 0.93, RMSEP = 2.86) for both calibration and prediction sets, respectively. The a* parameter most accurately predicted by using calibration (R^2 = 0.84, RMSEC = 0.09) and prediction (R^2 = 0.87, RMSEP = 0.11) developed from the image parameters of the Morris variety. The b* parameter displayed the lowest predictive ability for colour evaluation compared to L* and a* with the R^2 of 0.75 and RMSEP of 1.79 for the prediction set from the Josapine variety. The predictive ability of the models for colour parameters also achieved excellent results with RPD values higher than 3 and RER values higher than 12, respectively. As pineapple fruit ripening is a continuous process, the distinct colour restrictions between different ripening stages were quite difficult to define since the colour clearly changes throughout the maturation (Li et al., 2018). As a result, the good prediction performance found in all physicochemical properties of the pineapples indicated the capability of infrared thermal imaging in monitoring the quality attributes of the fruit.

3.4. Classification results using support vector machine

The classification performance of pineapple varieties at different storage days and temperatures using the SVM method is presented in Table 4. The promising SVM results were accounted based on the classification performance of pineapple varieties at 5 °C (95.02–99.62%), followed by 10 °C (94.96–99.62%), and 25 °C (95.25–99.36%), respectively. The classification accuracy of the SVM models was observed to increase over storage days for all pineapple varieties at different storage temperatures. The SVM models achieved the highest classification accuracies recorded at 25 °C for both Day 0 (97.18%) and Day 7 (98.34%) from the MD2 variety, respectively. The Josapine variety also obtained the highest classification accuracy at 25 °C (98.96%) and 5 °C (99.62%) for Day 14 and Day 21, respectively. The performance of the infrared thermal imaging technique based on SVM was found to be feasible which obtained overall classification rates of higher than 97% under different storage conditions for all pineapple varieties. These findings implied that the changes in image parameters of pineapple varieties associated with the variation in physicochemical properties of the fruit could be promising to be used in assessing various storage conditions.

In addition, the implementation of image parameters was performed in order to evaluate the ability of infrared thermal imaging technique for

Table 3
Calibration and prediction models based on image parameters of different pineapple varieties.

Variety	Quality Parameter	LVs	Calibration			Prediction			RPD	RER
			R^2	RMSEC	Bias	R^2	RMSEP	Bias		
MD2	TSS	7	0.79	1.15	1.85×10^{-6}	0.83	1.74	−0.15	4.63	13.63
	pH	7	0.91	0.10	0.01	0.94	0.09	1.13×10^{-8}	3.84	12.14
	Firmness	7	0.82	0.19	2.68×10^{-3}	0.87	0.04	1.98×10^{-8}	5.67	14.89
	MC	7	0.87	0.59	−0.04	0.92	0.47	-7.26×10^{-7}	3.58	12.56
	L*	6	0.89	3.48	0.23	0.93	2.86	1.95×10^{-6}	4.61	13.90
	a*	6	0.76	0.15	−0.01	0.83	0.10	1.43×10^{-7}	4.36	13.75
	b*	4	0.67	2.07	-2.78×10^{-3}	0.78	2.00	6.81×10^{-8}	3.68	12.63
Josapine	TSS	7	0.73	1.69	−0.13	0.81	1.22	1.95×10^{-6}	3.90	12.65
	pH	7	0.85	0.14	0.06	0.90	0.11	-3.40×10^{-7}	4.79	14.59
	Firmness	7	0.84	0.06	0.03	0.89	0.05	-1.22×10^{-7}	5.24	12.01
	MC	7	0.81	0.72	−0.05	0.88	0.56	4.54×10^{-7}	3.84	13.86
	L*	6	0.83	4.41	0.26	0.88	3.54	7.44×10^{-6}	3.21	12.57
	a*	6	0.70	0.15	−0.01	0.80	0.11	1.94×10^{-7}	3.75	12.45
	b*	4	0.66	2.53	−0.21	0.75	1.79	2.00×10^{-6}	4.97	12.33
Morris	TSS	7	0.74	1.51	−0.05	0.81	1.11	1.32×10^{-6}	5.03	12.64
	pH	7	0.84	0.18	−0.06	0.92	0.10	-9.37×10^{-8}	4.24	13.89
	Firmness	7	0.87	0.07	−0.02	0.91	0.04	1.56×10^{-8}	4.05	14.32
	MC	7	0.77	0.84	0.02	0.88	0.50	-5.44×10^{-7}	3.87	13.99
	L*	6	0.89	3.48	−0.01	0.91	3.34	1.11×10^{-6}	3.78	12.53
	a*	6	0.84	0.09	1.15×10^{-7}	0.87	0.11	0.08	3.96	12.98
	b*	4	0.75	1.89	0.01	0.83	1.78	2.72×10^{-6}	3.12	13.75

TSS: Total soluble solids, **MC**: Moisture content, **LV**: Latent variables, $\mathbf{R^2}$: Coefficient of determination, **RMSEC**: Root mean square error of calibration, **RMSEP**: Root mean square error of prediction, **RPD**: Ratio of performance to deviation, **RER**: Ratio of error range.

Table 4
The classification performance of pineapple varieties at different storage days and temperatures using support vector machine.

Variety	Temperature	Classification accuracy (%)				Overall Classification Rate (%)
		Day 0	Day 7	Day 14	Day 21	
MD2	5 °C	96.42	97.01	98.29	98.98	97.68
	10 °C	95.99	96.76	97.73	98.29	97.19
	25 °C	97.18	98.34	98.36	99.36	98.31
Josapine	5 °C	95.02	96.86	98.79	99.62	97.57
	10 °C	95.28	95.96	98.38	99.34	97.24
	25 °C	96.32	96.74	96.96	96.29	97.83
Morris	5 °C	95.26	96.13	98.90	99.47	97.44
	10 °C	94.96	96.62	98.87	96.62	97.52
	25 °C	95.25	96.11	98.92	98.93	97.30

simultaneous classification in different pineapple varieties under various storage conditions. The results showed that the SVM classifier trained on MD2, Josapine, and Morris generalised well despite having different varieties. Apart from that, it was observed that there was no significant effect in terms of model generalisation via the reduction of the number of features used by the SVM classifier since the classification performance was similar for all pineapple varieties. However, the optimisation performance of infrared thermal imaging measurements should enhance the discrimination capability in order to distinguish pineapple varieties according to the storage days and temperatures. The benefit of the infrared thermal imaging technique to visualise the differences in physicochemical properties could assist in developing the processing operation of pineapples as well as improve the characterisation of fruit ripening. Thus, the SVM method could effectively classify pineapple varieties using the infrared thermal imaging technique which is beneficial to enhance the detection of pineapple quality in preventing postharvest losses.

4. Conclusion

The current study evaluated the feasibility of infrared thermal imaging for the assessment of pineapple quality of different varieties during storage. The results revealed that the infrared thermal imaging technique based on image parameters can successfully predict the physicochemical properties of different pineapple varieties during storage, especially fruit stored at 10 °C. The optimal relations among all the image parameters successfully explained the robustness of the PLS models. Further, the PLS model demonstrated a good performance of quality prediction of pineapples with R^2 values of up to 0.94. The infrared thermal imaging technique works efficiently in distinguishing the variations in the physicochemical properties of pineapple varieties with the overall classification accuracies of more than 97% using the SVM method. The ability of infrared thermal imaging for classifying the pineapple varieties based on the physicochemical properties of the fruit was encouraging as a potential tool under different storage conditions. Hence, an advanced undertaking in exploiting the feasibility of infrared thermal imaging is required to be implemented for real-time and online automated fruit grading systems.

CRediT authorship contribution statement

Maimunah Mohd Ali: Data curation, Investigation, Software, Writing – original draft, preparation, Visualization. **Norhashila Hashim:** Supervision, Validation, Writing – review & editing. **Samsuzana Abd Aziz:** Supervision, Formal analysis. **Ola Lasekan:** Supervision, Conceptualization.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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