Milk Spoilage Classification through Integration of RGB and Thermal Data Analysis

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Abstract: In Malaysia, milk consumption is commonly associated with family households, specifically children. The nutrition in milk is fundamental for children's growth which is why the parents will ensure their children have adequate milk intake from an early age. Various kinds of milk are available on the market, but pasteurized milk and UHT milk are the most consumed. Without proper storage and packaging conditions, milk could spoil quickly; hence an early detection method is needed to detect milk staleness and spoilage. Much research and study has been done regarding the classification of milk spoilage. However, factors such as the unreliability of data and time-consuming methods prove that a better working model with high accuracy needs to be developed. Efficient detection methods are crucial for ensuring milk quality. This project is targeted to develop and introduce image-based analysis to detect the spoiled milk in various packaging and storage conditions using Deep Learning and Python programming language to cater for the problem stated above. A dataset containing both RGB and thermal images of milk was self-obtained. The proposed model in this paper has achieved the accuracy of 99% for classification of RGB images of milk and 98% for the thermal images of milk.

Keywords: classification, deep learning, milk spoilage, RGB image, thermal image.

1. Introduction

The study of food in deep learning has been available for a long time such as studying fruits and vegetables. Nowadays, despite these earlier two foods, other types of food and even ingredients are being involved in deep learning such as milk. In Malaysia, milk consumption is commonly associated with family households, specifically children. The nutrition in milk is fundamental for children's growth so the parents will ensure their children have adequate milk intake from an early age, making milk a staple food. For the first six months of life in a child, they were advised to exclusively being fed breastmilk. After the age of six months, non-human milk commonly cow milk is consumed to aid in the child's growth. The nutrition in milk such as calcium, proteins, high level of energy, micronutrients and macronutrients and insulin-like growth factor-1 (IGF-1) are beneficial in a child's development. In 1928, a study conducted by Boyd Orr had shown that Scottish children ranging from the age of 5 to 14 years old that had consumed milk other than their normal diet had a 20% increase in their height and weight [1].

Fig. 1 below shows the production and consumption of milk from the year 2011 until 2017. In Malaysia, the production is rather slow compared to the consumption. The production of milk gradually increases between 2011 and 2017 which opposes to milk consumption in Malaysia that had climbed approximately four times [2].

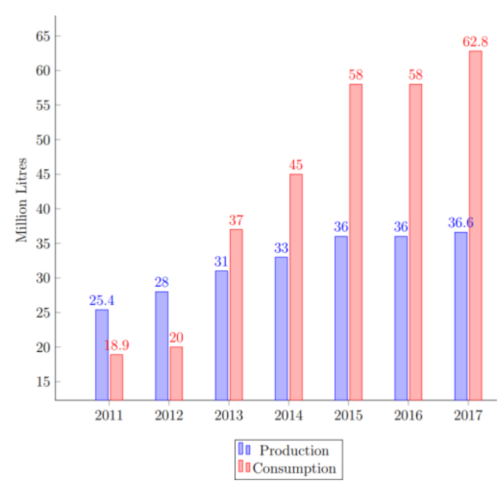


Figure 1. Milk production and consumption from the year 2011 until 2017 [2].

In 2011, milk production was found to be at 25.40 million litres and the count increased by 11.20 million litres in 2017 with milk production of 36.60 million litres. Meanwhile, milk consumption drastically increases as much as 44.10 million litres within the same timeline. The milk consumption was recorded to be at 18.90 million litres in 2011 and in 2017 it had become 62.80 million litres. Now, the expanding demand for milk and other milk-related products in Malaysia has changed due to changes in customer tastes, rising incomes, and increased knowledge of the products' nutritional advantages. [2].

In recent years, numerous methods have been used to detect spoiled milk which are considered viable for research and studies. One of the methods discussed is by using chemical sensors or biosensors. The growth of microorganisms in milk will cause modification to happen to the medium's composition through their metabolic products, as well as the pH, conductivity, ionic content, color, odor, viscosity, and other milk’s physicochemical characteristics. Hence, chemical sensors and biosensors come into place as a great deal of research has been done on chemical and biosensors as viable substitutes for the current standard techniques for detecting milk quality [3]. As mentioned by International Union of Pure and Applied Chemistry (IUPAC), the chemical sensors are often made up of two fundamental parts that are connected in series, which are a physico-chemical transducer and a chemical (molecular) recognition mechanism, or receptor [3].

Meanwhile, biosensors are the same as chemical sensors except a biochemical mechanism is used as the recognition system. The biological recognition system, often called a bioreceptor, uses data from the biochemical domain, frequently an analyte concentration, to produce a physical or chemical output signal with a defined sensitivity. Chemical sensors and biosensors can be categorized based on the types of transducers employed, the biochemical recognition element used for detection, or the analytes to be detected. The beneficial traits of these sensors such as fast response time, high sensitivity, small in size and with little to no sample preparation make them suitable for the use of detecting milk spoilage [3].

Besides chemical sensors and biosensors, pH value is a famous parameter for detecting milk spoilage. The growth of bacteria differs from one species to another. One type of bacteria may thrive in some conditions while others may weaken. At approximately 6.7 in pH level, milk is considered to be unspoiled or still in good condition. Some bacteria may also thrive at this pH level. However, as the pH level goes lower to a range of 4.0 to 5.0, lactic acid may be produced due to its bacteria growing [4]. With this information, any appropriate pH meter can be used to determine the condition of milk.

Next, is the use of methylene blue reduction test which is an electrical method that can be used to detect bacteria. In this test, an appropriate amount of methylene blue solution was added to a milk sample and the sample was then placed in water bath at certain temperatures. Time taken for the methylene blue color to reduce is recorded and whichever milk samples take a longer time for reduction means the milk is of good quality. In other words, the slower the time taken for reduction, the better the milk condition is [5]. Although methylene blue reduction test can be used to determine the quality of milk, it is however very time consuming and repetitive procedures [4].

Finally, image processing technique were used to detect spoiled milk. Image processing is digitally converting an image and carrying out the necessary operations to obtain helpful information. Combining image processing with artificial intelligence or deep learning can be one method used to detect spoiled milk [6]. A dataset of images is created by taking an appriopriate number of images of milk bottles that contain both good and spoiled milk. A model is created, and the dataset of images will then be used to train and test the model. The model will then predict the condition of milk to be either good or spoiled, based on the images given [7].

The emerging use of food and ingredients in research nowadays calls for the study of milk. Given that in Malaysia, there are many techniques that can be applied in the study of classification of milk spoilage. One of the possible techniques that can be applied as discussed above is the use of image data analysis. Both RGB image data and thermal image data can be used in this study.

The objectives of this study are to prepare dataset containing RGB images of milk and thermal images of milk, to develop a classification model for detecting spoiled milk in various storage conditions and to analyze and detect spoiled milk via multiple models to compare accuracy with proposed model.

2. LITERATURE REVIEW

This literature review focuses on the classification of milk spoilage utilizing deep learning methods and the use of RGB image and thermal image as the datasets. Researchers have explored various deep learning architectures to accurately identify and classify spoilage patterns in milk samples. Studies have focused on pre-processing techniques to enhance the quality of input data, including image enhancement and feature extraction algorithms tailored to milk spoilage characteristics.

Furthermore, researchers have examined the transferability of deep learning models trained on one dataset to unseen datasets.

The pH values of milk in both good and spoiled condition are also discussed to ensure that the images collected in this project are labeled correctly according to their condition. Overall, the literature underscores how deep learning techniques can transform the way that milk deterioration is detected and classified, creating a path for more dependable and effective quality control measures in the dairy industry.

A. *pH Values of Good and Spoiled Milk*

A study on Development and Optimization of Dynamic Gelatin/Chitosan Nanoparticles Incorporated with Blueberry Anthocyanins for Milk Freshness Monitoring by Yanlan Maet al. (2020) was conducted and in the study the pH values of milk were mentioned. It was mentioned that when milk deteriorates, the quantity of bacteria in the milk increases. Hence, resulting in decreasing pH values. Table I below shows the pH values of milk in good and spoiled condition [8].

TABLE I. PH VALUES OF MILK [8].

Milk Condition	**pH Values**
Fresh milk	6.6 – 6.8
Spoiling	5.5 – 6.0
Spoiled	4.5 – 5.5

Based on a study done by Max Weston et al. (2020) on Anthocyanin-based Sensors Derived from Food Waste as an Active Use-by Date Indicator for Milk, pH value is one of the best approaches to monitor milk spoilage as pH since its reaction to bacterial growth is least dependent on the type of bacteria. There is still no definitive value of pH where the milk is not safe to consume which in turn limits the designing of a freshness detection method using pH value. It was agreed that the pH values of milk in good and spoiled condition are as in Table II below [9].

TABLE II. PH VALUES OF MILK [9].

Milk Condition	**pH Values**
Fresh milk	~ 6.8
Spoiled	< 4.5

A study on Incorporation of Gelatin and Fe2+ Increases the pH-sensitivity of Zein-Anthocyanin Complex Films Used for Milk Spoilage Detection by Ruichang Gao et al. (2022) states that pH value of milk decreases when milk is spoiling because lactic acid bacteria break down lactose which in turn produces lactic acid. Table III below shows the pH values of milk in good and spoiled condition [10].

TABLE III. PH VALUES OF MILK [10].

Milk Condition	**pH Values**
Fresh milk	6.6 – 6.8
Spoiled	4.0 – 5.0

B. *Classification and Detection of Milk Spoilage*

Based on research done by Daniel Rodriguez et al. (2020), WPT/NFC coil is used to record data from fresh milk and spoiled milk. In this research, it is believed that when raw milk expires, its electrical properties change. As the beverage bottle moves towards the coil, it generates induced eddy currents and electromotive force within it, causing a shift in the coil's impedance. These alterations occur from differences in the resistivities and dielectric constants between the surrounding air and the beverage bottle. Hence, the detection method can be done based on the dielectric constant correlation [11]. However, since the data collected is not directly from the milk itself but from the milk carton, the accuracy of the testing may not represent the real condition or freshness of the milk. Other than that, more research is required to determine the impacts of various milk storage conditions and packaging types in order to develop a more comprehensive classification system.

A study on Miniaturized Milk Adulteration Detection System by Suryasnata Tripathy et al. (2018) is conducted to develop a compact and cost-effective platform designed for monitoring the natural physical characteristics of milk. to detect milk adulteration. Other than adulteration, microbial spoilage is also proven to increase the acidity of milk which will give a lower reading of pH value. In this study, pH sensor strip is used to identify milk spoilage. Every milk sample underwent individual testing utilizing a minimum of 15 sensor strips. Precisely, each strip was immersed into the milk sample, allowed to adequately dry, and then captured using a smartphone camera. Subsequently, the areas on the sensors showing color changes were cropped from the images and associated with respective pH values. The samples are then labelled with values in the range 6.6–6.9 as pure (class label 1), < 6.6 as acidic (class label 0), and > 6.9 as basic (class label 2) [12]. However, collecting data of pH value using image of each sensor strip is time consuming considering each sensor strip needs to be captured. Using pH value instead of pH strip colour is more time efficient.

C. *Classification Approach with RGB Images*

A study on Fruit Disease Classification and Identification using Image Processing is conducted by Ayyub et al. (2019) to identify apple fruit disease. The dataset consists of a total of 280 apple fruit images of different conditions. The images vary such as rot, scab, blotch, and normal apple where each class contains 70 apple fruit images. Image segmentation, feature extraction and feature combination are conducted before classification. The classifier chosen for the study is Multi-Class Support Vector Machine (MSVM). Features that were used to identify and classify the diseased and normal apple fruit were color coherence vector (CCV), zernike moments (ZM), improved sum and difference histogram (ISADH), completed local binary pattern (CLBP) and gray level co-occurrence matrix (GLCM). After accuracy percentage is calculated, 96.07% average classification accuracy was achieved by using ISADH+GLCM and 96.29% average classification accuracy achieved by using ISADH+CLBP+ZM features combination. Considering that RGB images are the only type of data collected, using MSVM only may not be satisfying. Multiple models can be used to have various accuracy results. Hence, the best model can be chosen based on the accuracy percentage [13].

D. Classification Approach with Thermal Images

A study on Deep Learning-Based Plant Classification and Crop Disease Classification by Thermal Camera by Batchuluun, G et al. (2022) is conducted, and the proposed method used is Convolutional Neural Network (CNN) where plant diseases and crop diseases is classified by using thermal images as data, accompanied by Explainable Artificial Intelligence (XAI), the proposed method is called Plant Deep Explainable Artificial Intelligence (PlantDXAI). Two datasets were used in this study which were their thermal plant image dataset which was self-obtained and an open database of crop diseases which were the paddy crop dataset. To enlarge the paddy crop open database, they applied image augmentation to the 447 training images [14].

The augmentation was done by flipping the images horizontally and rotating the images by 90° three times. In total, they managed to obtain 3,576 images for the open database. As for their self-obtained thermal plant image dataset, they used a Tau® 2 FLIR thermal camera and captured various images of roses and rose leaf. To enlarge their self-obtained thermal plant image dataset, they applied image augmentation to 3,314 training images. The augmentation was done by flipping the images horizontally and rotating the images by 90° three times. In total, they managed to obtain 26,512 images for the self-obtained thermal plant image dataset which has 28 classes in total. For plant image classification using self-obtained thermal plant image dataset, CNN-16 obtained the average accuracy of 98.55%. As for crop disease image classification using paddy crop open database, CNN-16 obtained the accuracy of 88.63% without Class Activation Map (CAM) and 90.04% with CAM [14].

3. METHODOLOGY

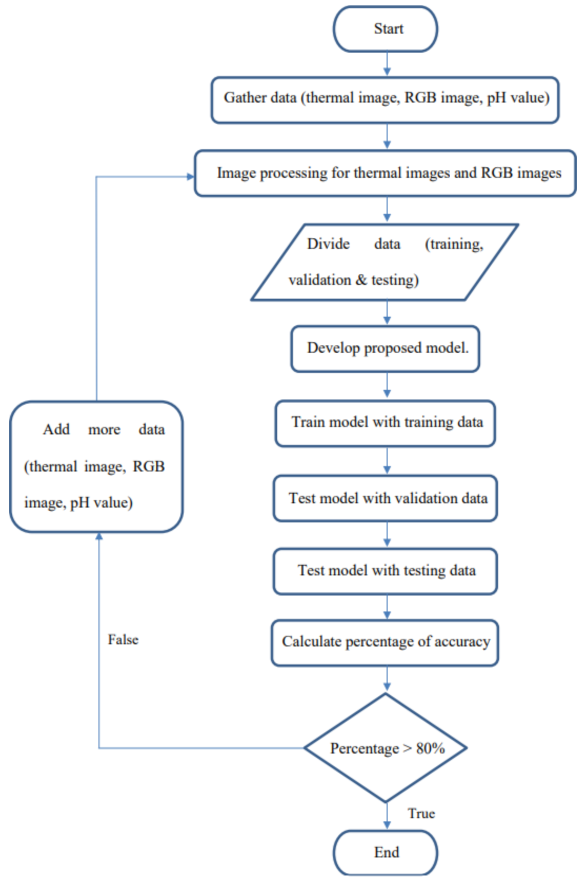


Figure 2. Flowchart of methodology.

Fig. 2 above shows the overall flowchart of the methodology that is carried out in this project. Firstly, sample preparation is done to create two datasets for this study. RGB images of milk and Thermal images of milk will be used as data for the model. The datasets are RGB image dataset which contains RGB images of milk and thermal image dataset which contains thermal images of milk.

To prepare dataset for this study, sample needs to be prepared for thermal image, RGB image and pH value collection. To ensure reliability and consistency of data, the same brand of milk was used throughout this study. The sample was prepared according to Table IV shown below.

TABLE IV. PREPARATION OF SAMPLES.

Carton Condition	Table Column Head	Time Left (Hours)
Perfectly sealed carton	Refrigerated	24, 48, 72, 96
	Room Temperature	
Holed carton	Refrigerated	24, 48, 72, 96
	Room Temperature	
Opened carton	Refrigerated	24, 48, 72, 96
	Room Temperature	

In this sample preparation, one milk carton was used per category. For example, one perfectly sealed carton is placed in the refrigerator for 24 hours. Another one perfectly sealed carton is placed in the refrigerator for 48 hours and so on. There was a total of 24 milk cartons used in this study. For perfectly sealed carton, the cartons were placed in their respective category as it is. While for holed carton, a hole was made at the foil protector on top of the milk carton where the straw was supposed to go in. Lastly, for opened carton, the top of the carton was cut open entirely to be left exposed.

When the sample had reached its time mark, thermal image and RGB image of the sample were captured. A thermal camera was used to capture thermal image while an Android phone camera, Samsung J6 model was used to capture RGB image. To maintain quality of data and to avoid overexposure of light from surrounding area, the image for all sample were captured in the same room and a lightbox was utilized. The sample was first poured into a glass cup, then the glass cup is placed inside the lightbox. The pH values of milk from each sample will be recorded every time RGB and thermal image are captured with the size of 3096x4128 pixel and 240x240 pixel respectively. The pH values will not be included in the dataset because the pH values only serve the purpose of determining whether the milk is still good or already spoiled.

To enlarge both datasets, image processing method will be applied to both RGB and thermal images captured. Both RGB and thermal images will then be grouped into two different classes which are ‘Spoiled’ and ‘Good’. A random set of images for both RGB and thermal image are collected to create a third class called ‘Unclassified’. In total, each dataset contains three classes which are ‘Spoiled’, ‘Good’ and ‘Unclassified’. The number of images in RGB and thermal image dataset is the same which were 963 images. The splitting percentage used were 70% for training dataset, 15% for validation dataset and 15% for testing dataset. Table V below shows the number of images in the three datasets.

TABLE V. THE NUMBER OF IMAGES IN THE THREE DATASETS.

Dataset	RGB Image	Thermal Image
Training (70%)	675	675
Validation (15%)	144	144
Testing (15%)	144	144
TOTAL (100%)	**963**	**963**

Fig. 3a), 3b), 3c) and 3d) and Fig. 4a), 4b), 4c) and 4d) below show the example of RGB images of milk and thermal images of milk captured.

a) b)

c) d)

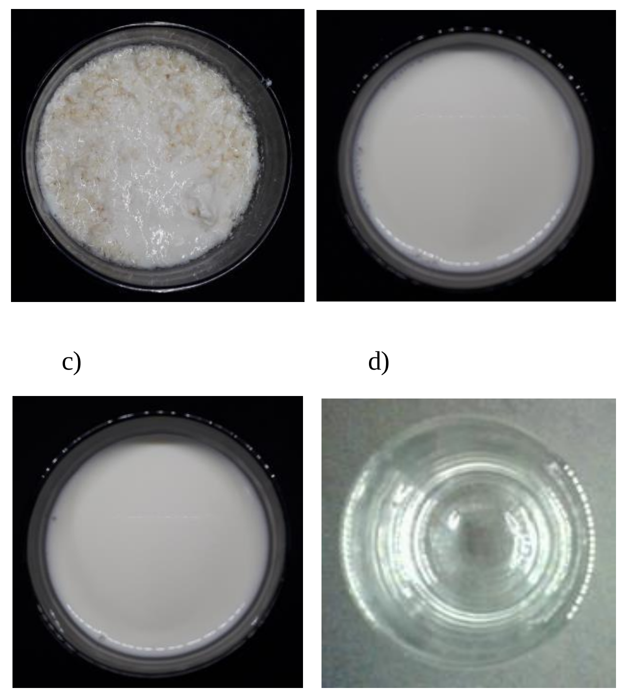
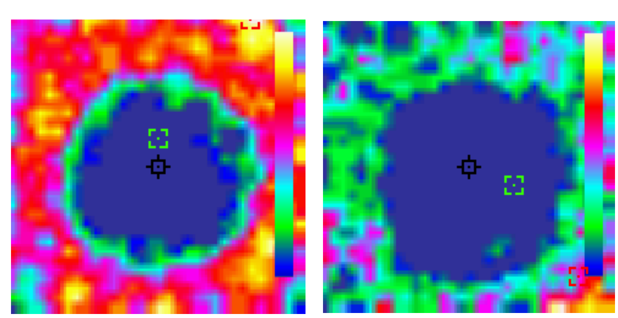


Figure 3. RGB images of milk: a) spoiled milk at room temperature, b) good milk at room temperature, c) milk in refrigerator, d) unclassified

a) b)



c) d)

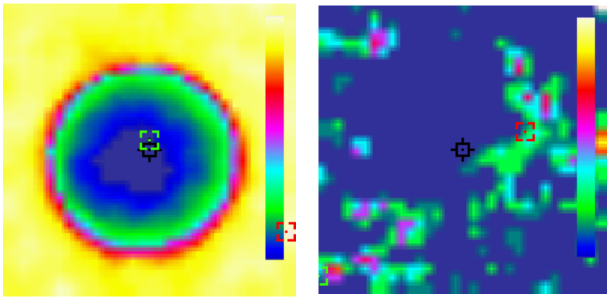


Figure 4. Thermal images of milk: a) spoiled milk at room temperature, b) good milk at room temperature, c) milk in refrigerator, d) unclassified

The proposed model used in this study is Convolutional Neural Network (CNN) and the layers in this model is shown in the model summary in Fig. 5 below.

Layer (type)	Output Shape
conv2d (Conv2D)	(None, 238, 53, 32)
conv2d_1 (Conv2D)	(None, 236, 51, 64)
max_pooling2d (MaxPooling2D)	(None, 118, 25, 64)
dropout (Dropout)	(None, 118, 25, 64)
conv2d_2 (Conv2D)	(None, 116, 23, 128)
max_pooling2d_1 (MaxPooling2D)	(None, 58, 11, 128)
conv2d_3 (Conv2D)	(None, 56, 9, 128)
max_pooling2d_2 (MaxPooling2D)	(None, 28, 4, 128)
dropout_1 (Dropout)	(None, 28, 4, 128)
flatten (Flatten)	(None, 14336)
dense (Dense)	(None, 1024)
dropout_2 (Dropout)	(None, 1024)
dense_1 (Dense)	(None, 3)

Figure 5. Model summary.

Multiple layers were added to the model to create the proposed classification model. The first two layers added to the model were a 2D convolution layer which usually abbreviated as conv2D. Next, max pooling 2D layer of most known as MaxPooling2D was added where it will choose the highest value from every pool. Then, dropout layer was added where it will randomly ignore some nodes in the layer during training. Conv2D and MaxPooling2D were added two more times followed by a dropout layer. Afterwards, a flatten layer was introduced to convert the pooled feature map into a singular column, which was then passed to the fully linked layer. The fully connected layer was integrated into the neural network using a dense layer. Finally, an additional dropout layer and dense layer were appended to the model. The summary of the model was then printed out.

4. Results, Analysis and Discussion

To evaluate the performance of the developed proposed model, have a look at its percentage of accuracy. Fig. 6 and Fig. 7 below show the comparison of accuracy percentages between the developed proposed model and with VGG16, VGG19 and ResNet for RGB and thermal image dataset respectively. It can be seen that for both RGB and thermal image dataset, the developed proposed model is able to achieve the highest accuracy percentage compared to all the other models involved in this study.

Other than percentage of accuracy, precision, recall and F1-score which can be obtained from the classification report can also be used to evaluate the performance of the developed proposed model. Support in the classification result is the number of samples that belong to each three classes.

A. Results for RGB Image Dataset

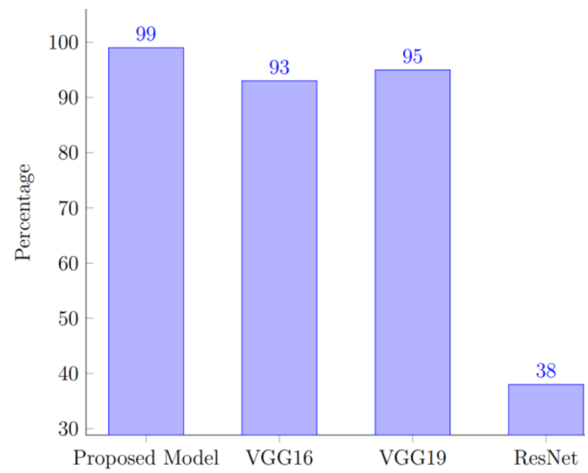


Figure 6. Accuracy percentages between the developed proposed model and with VGG16, VGG19 and ResNet for RGB.

The proposed model in this study has achieved an accuracy of 99% while VGG16 model has achieved an accuracy of 93%. The VGG19 model has achieved an accuracy of 95%. And lastly, the ResNet model has achieved an accuracy of 38%. Table VI below shows the classification report for the proposed model.

TABLE VI. CLASSIFICATION REPORT FOR PROPOSED MODEL (RGB).

Class	Precision	Recall	F1-score	Support
Class 1 (Spoiled)	0.96	1.00	0.98	48
Class 2 (Good)	1.00	0.96	0.98	48
Class 3 (Unclassified)	1.00	1.00	1.00	48

For proposed model, Class 2 and Class 3 both have the same precision and were higher than Class 1, which proves that the model correctly identified all positive outcomes for Class 2 and Class 3. While for recall, Class 1 and Class 3 have the highest recall, leaving Class 2 with 0.96. The majority of the dataset's positive occurrences for Class 1 and Class 3 are captured by the model. F1-score are the combination of precision and recall. As Class 3 has a perfect score of 1.0 for precision and recall, it automatically gained the F1-score of 1.0 while Class 1 and Class 2 gained F1-score of 0.98.

Table VII, VIII and IX below shows the classification report for the VGG16, VGG19 and ResNet respectively.

TABLE VII. CLASSIFICATION REPORT FOR VGG16 (RGB).

Class	Precision	Recall	F1-score	Support
Class 1 (Spoiled)	1.00	0.79	0.88	48
Class 2 (Good)	0.84	1.00	0.91	48
Class 3 (Unclassified)	0.98	1.00	0.99	48

TABLE VIII. CLASSIFICATION REPORT FOR VGG19 (RGB).

Class	Precision	Recall	F1-score	Support
Class 1 (Spoiled)	1.00	0.85	0.92	48
Class 2 (Good)	0.87	1.00	0.93	48
Class 3 (Unclassified)	1.00	1.00	1.00	48

TABLE IX. CLASSIFICATION REPORT FOR RESNET (RGB).

Class	Precision	Recall	F1-score	Support
Class 1 (Spoiled)	0.35	0.15	0.21	48
Class 2 (Good)	0.00	0.00	0.00	48
Class 3 (Unclassified)	0.39	1.00	0.56	48

B. *Results for Thermal Image Dataset*

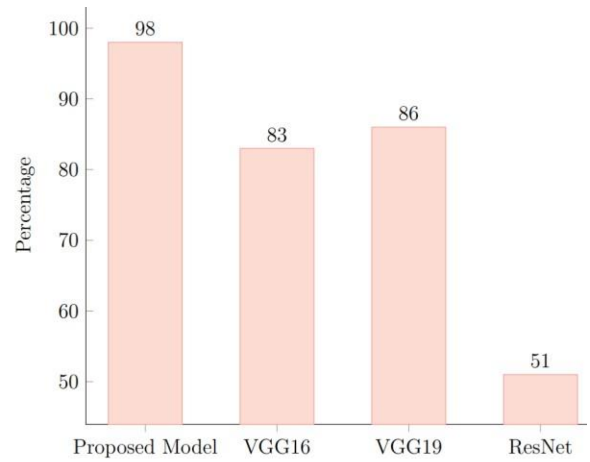


Figure 7. Accuracy percentages between the developed proposed model and with VGG16, VGG19 and ResNet for thermal.

The proposed model in this study has achieved an accuracy of 98% while VGG16 model has achieved an accuracy of 83%. The VGG19 model has achieved an accuracy of 86%. And lastly, the ResNet model has achieved an accuracy of 51%. Table X below shows the classification report for the proposed model.

TABLE X. CLASSIFICATION REPORT FOR PROPOSED MODEL (THERMAL).

Class	Precision	Recall	F1-score	Support
Class 1 (Spoiled)	0.94	1.00	0.97	48
Class 2 (Good)	1.00	0.94	0.97	48
Class 3 (Unclassified)	1.00	1.00	1.00	48

For proposed model, Class 2 and Class 3 both have the same precision and were higher than Class 1, which proves that the model correctly identified all positive outcomes for Class 2 and Class 3. While for recall, Class 1 and Class 3 have the highest recall, leaving Class 2 with 0.94. The majority of the dataset's positive occurrences for Class 1 and Class 3 are captured by the model. F1-score are the combination of precision and recall. As Class 3 has perfect score of 1.0 for precision and recall, it automatically gained the F1-score of 1.0 while Class 1 and Class 2 gained F1-score of 0.97.

Table XI, XII and XIII below shows the classification report for the VGG16, VGG19 and ResNet respectively.

TABLE XI. CLASSIFICATION REPORT FOR VGG16 (THERMAL).

Class	Precision	Recall	F1-score	Support
Class 1 (Spoiled)	1.00	0.50	0.67	48
Class 2 (Good)	0.69	1.00	0.81	48
Class 3 (Unclassified)	0.96	1.00	0.98	48

TABLE XII. CLASSIFICATION REPORT FOR VGG19 (THERMAL).

Class	Precision	Recall	F1-score	Support
Class 1 (Spoiled)	0.71	1.00	0.83	48
Class 2 (Good)	1.00	0.79	0.88	48
Class 3 (Unclassified)	1.00	0.79	0.88	48

TABLE XIII. CLASSIFICATION REPORT FOR RESNET (THERMAL).

Class	Precision	Recall	F1-score	Support
Class 1 (Spoiled)	0.00	0.00	0.00	48
Class 2 (Good)	1.00	0.58	0.74	48
Class 3 (Unclassified)	0.40	0.96	0.57	48

5. LIMITATION

There were a few limitations observed during the run of this research which were room temperature or weather. Since the collection of data involves different number of days for the sample to be collected, the current weather could affect the room temperature which in turn could affect the spoiling rate of the milk sample. Next, lighting challenge during data collection which is capturing RGB image and thermal image. The surrounding area may emit different lighting at times which can cause shadows and color discrepancies. Hence, a lightbox was used as additional equipment to control the emition of light.

6. CONCLUSION

This study proposed a classification model in detecting the freshness of milk in various storage conditions. Two datasets which are RGB image dataset which contains RGB images of milk and thermal image dataset which contains thermal images of milk were self-obtained throughout this study. The highest percentage of accuracy has been successfully achieved by the proposed model in comparison to other chosen models which are VGG16, VGG19 and ResNet. For RGB image classification, the proposed model has an accuracy percentage of 99% while for thermal image classification, the proposed model has an accuracy percentage of 98%. In conclusion, all the objectives in this study are successfully achieved which are to prepare dataset containing RGB images of milk and thermal images of milk, to develop a classification model for detecting spoiled milk in various storage conditions and to analyze and detect spoiled milk via multiple models to compare accuracy with proposed model. There are many aspects in this study that can be improved such as the quality of images captured, size of dataset and variables used in classification. To obtain a better working classification model, images may be captured in various lighting conditions, not in controlled environments. Other than that, more images can be captured and apply image augmentation to the captured images to enlarge the dataset. Larger dataset will improve the classification model because the model will have large amount of data to learn from. Last but not least, milk does not only come in full cream type only, but it also comes in different flavours and varieties such as strawberry, chocolate, and low fat. This means more milk flavours and varieties can be added as variables for future work.

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