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Beef Quality Classification based on Texture and Color Features using SVM Classifier

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Abstract

Beef quality can be examined visually by observing the beef color or texture using human eyes. This manual method is very simple yet very subjective because of differences in knowledge about fresh or defective beef characteristics and differences in accuracy. Therefore, a system that can automatically classify beef quality whether it is still fresh or already defective is needed. In this research, we developed a system that can classify beef quality based on its color and texture features using Support Vector Machines classifier. Statistical approach and Gray Level Co-Occurrence Matrix (GLCM) methods were used for the feature extraction process. The total of data used in this research was 480 images, divided into training and testing datasets. The highest accuracy was 97% for cold beef when the system was tested using color features of HSI color space.

Keywords: *Beef quality, Statistical approach, GLCM, SVM.*

1. Introduction

The number of beef consumption in Indonesia has been increasing. Data from Indonesian Central Bureau of Statistics showed that the number of national beef consumption in 2016 reached 524,109 tons and this will keep increasing with the average increase of 1.93% each year [1].

A fresh beef contains many nutrients such as protein, zinc, vitamin B6, B12 and other nutrients that are good for health. Beef or other meat distribution process in Indonesia commonly takes several steps, started from the slaughterhouse, then distributed to the market and then to the consumers. This distribution process may take a lot of time which can cause the meat to lose its drip. This drip contains many nutrients such as protein, vitamin, and mineral. Therefore, the more drip loss, the lower the quality of the meat.

The quality of beef whether it is fresh or defective can be examined manually by visually observing its color and texture. It can also be identified by its smell. This method is very simple but the results may differ from one person to another depending on their knowledge of beef quality and also their accuracy. Therefore, an automated system for beef quality classification is needed.

This research aims to develop a system that can be used to classify beef quality based on its texture and color features. In this research, we attempted to classify the beef quality into three classes (fresh, half-fresh and defective) and also into two classes (fresh and defective) to find out which one gives a better accuracy using Support Vector Machines (SVM) classifier.

Related works about beef quality identification have been done earlier by some researchers. Various feature extraction methods have been used such as statistical approach [2],[3], GLCM [4], and color intensity [5]. Several classification methods can be used to classify the beef quality. Asmara et al. [6] compared the performance of Naïve Bayes and Decision Tree to classify the beef quality based on its color and texture feature. The research showed that Naïve Bayes obtained a better performance with the accuracy of 95.83%. Adi et al. [7] also proposed Decision Tree to identify the beef quality on an android based application using thresholding method. The accuracy obtained in this research was 90% for the training samples and 84% for the testing samples. Another research by Nunes et al. [8] aimed to obtain the beef quality estimation from the analysis of ultrasound and color images using Support Vector

Regression and several feature extraction methods i.e. gradient, co-occurrence matrix, gray level, histogram Fourier transform, and LBP. The proposed algorithm showed good results to calculate the rib area and the backfat thickness measure and profile. Xiao, Gao, and Shou [9] developed an online system to detect the freshness of pork using PNN Neural network. With the CRR feature, the system obtained an accuracy of 88%.

These researches have performed high accuracies in identifying the beef quality. However, these researches did not separate between the beef that was stored in a room temperature and the cold beef. A fresh beef is a beef that has just been slaughtered and has not received any other treatment, while a cold beef is the a newly slaughtered beef and received a chilling process until the temperature is about 0-7ºC [10]. Therefore, in this research, we use two kinds of datasets, the first dataset is the normal beef or the beef that is only stored in the room temperature without any treatment and the second is the cold beef that is stored in the fridge to get chilled.

2. Research Method

In the testing process, we use some parameters to find out how they affect the accuracy. These parameters are the number of class, image resolution, and image rotation.

2.1. Approach

In this research, we use the common pattern recognition processes as shown in Figure 1.

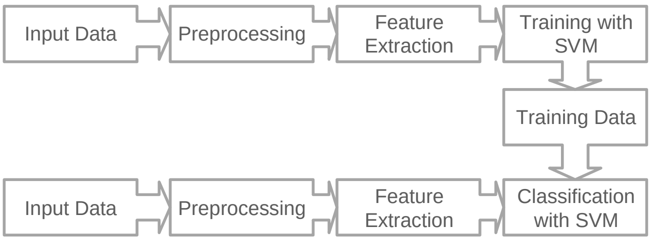


Figure 1. Research approach

The first step is image pre-processing by cropping the images, followed by resizing and then color space conversion. Each image is cropped to get the beef image without any background and then resized with the size of 128x128 pixel, 256x256 pixel, and 512x512 pixel. Each image then converted from RGB to HSI, YCbCr, and grayscale images. HSI and YCbCr images are used for color feature extraction while grayscale is used for texture feature extraction. As for the feature extraction, the statistical approach is used to extract the color features and Gray Level Co-Occurrence Matrix (GLCM) for texture feature extraction. Features from both methods are then trained using Support Vector Machines (SVM) method. The training result is saved and used in the classification process which involves the same processes as the training process.

2.2. Data Collection

The beef images are taken from 4 different beef samples to make the data more various. Each sample is then sliced into two pieces and we store the first piece in the fridge and the other in room temperature. The room temperature and fridge beef samples are stored for 27 and 55 hours respectively. Images of each sample are taken using DSLR camera in every 2 hours for beef in room temperature and every 5 hours for beef in the fridge. Table 1 shows the image examples of beef in the fridge based on the data collection time. In this process, 480 images of beef are collected. The quality categories are determined based on the length of storage time. The dataset distribution is given in Table 2.

Table 1. Data collection of beef in the fridge (cold beef)

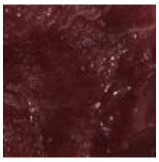
Image					
Hour	1	5	9	13	18
Image					
Hour	19	23	27	31	36
Image					
Hour	37	41	46	50	55

Table 2. Dataset distribution

Room Temperature Beef	Fresh	80
	Half-fresh	80
	Defective	80
Cold Beef	Fresh	80
	Half-fresh	80
	Defective	80
Total		**480**

Datasets for each class are split into training and testing data with the total of 60 and 20 data respectively. The classification using 2 classes consisted of fresh and defective beef, while the halffresh class images are defined as defective.

2.3. Preprocessing

The image preprocessing takes several steps as shown in Figure 2. The first step is cropping the image to cut the background image and only take the beef image. All images are cut and then resized with the size of 128x128 pixel, 256x256 pixel, and 512x512 pixel. We resized the image into 3 different sizes to find out the effect of image resolution on the accuracy. This process is done outside the system to minimize the computation processes.

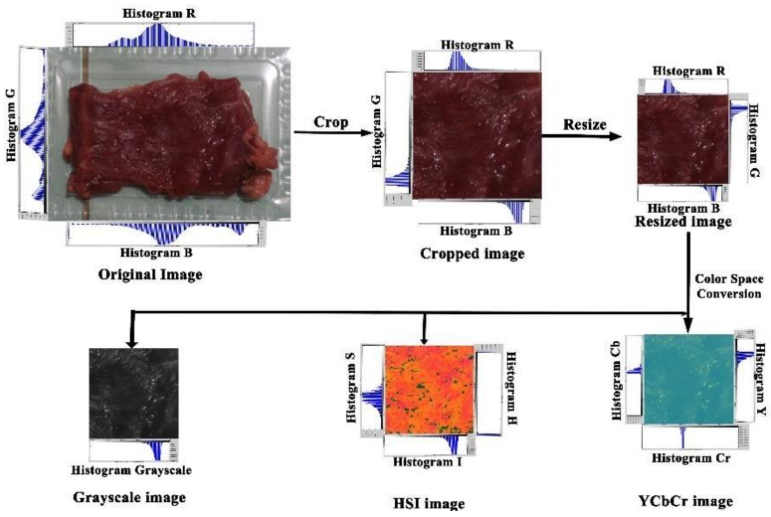


Figure 2. Image preprocessing

The color space conversions are conducted from RGB to HSI, RGB to YCbCr and RGB to grayscale. HSI color space defines colors in Hue, Saturation, and Intensity. Hue represents the real color, saturation refers to the intensity of color in an image, and intensity represents the amount of light that is received [11]. RGB to HSI conversion formulas are shown in the equation (1) to (4).

$$H = \begin{cases} \theta & jika\ B \leq G \\ 360 - \theta & jika\ B > G \end{cases} \tag{1}$$

with

$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{\frac{1}{2}}}\right\} \tag{2}$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)] \tag{3}$$

$$I = \frac{R+G+B}{3} \tag{4}$$

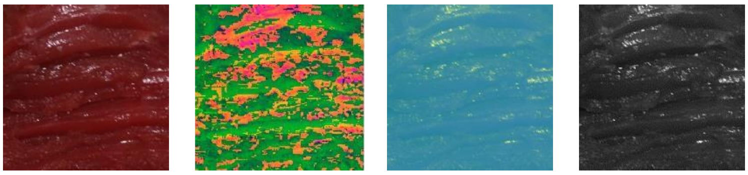
On the other side, YCbCr color space consists of Y, Cb, and Cr components. Luminance information is represented by a single component, *Y*, and color information is stored as two colordifference components, *Cb* and *Cr* [12]. RGB to YCbCr conversion formula is shown in the equation (5).

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112 \\ 112 & -93.786 & -18.214 \end{bmatrix}\begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{5}$$

The image in grayscale color space used for texture feature extraction using GLCM method. As for the RGB to the grayscale conversion formula is shown in the equation (6).

$$Grayscale = 0.2989 * R + 0.5870 * G + 0.1140 * B \tag{6}$$

Figure 6 shows the example of an image in RGB color space converted to HSI, YCbCr, and grayscale image. These images are used in the feature extraction process.



(a) (b) (c) (d)

Figure 3. (a) RGB, (b) HSI, (c) YCbCr, (d) Grayscale

2.4. Feature Extraction

Feature extraction is conducted to obtain color and texture features. Color features are extracted using statistical approach while texture features are extracted using GLCM method.

2.4.1. Color Feature Extraction using Statistical Approach

Statistical mean, median, mode, and variance are computed from each image in both HSI and YCbCr color space. Each statistical feature is extracted from each channel in HSI and YCbCr formats. a. Mean

Mean is the average of all numbers. Statistical mean is calculated using the following formula:

$$\bar{x}=(\textstyle\sum_i \frac{x_i}{n}$$

(7) b. Median

Median is the middle score in a sequence number. If the total number is even, then the median is calculated as the average of the two middle number.

c. Mode

Mode is the number that occurs most often within a set of numbers.

d. Variance

Suppose that we have n number of data from x1,x2…xn, and x' is the mean, then variance can be calculated with the following formula:

$$s^2 = \frac{\sum(xi-\bar{x})^2}{n-1} \qquad (8)$$

This color feature extraction obtaines 12 features for both HSI and YCbCr color space.

2.4.2. Texture Feature Extraction using GLCM

Gray Level Co-Occurrence Matrix (GLCM) which is one of the methods for texture feature extraction was initially proposed in 1973 by Haralick et al. [13]. There are 14 textural features that can be extracted using this method, but in this research, we only use 5 out of 14 textural features.

The first step of GLCM method is generating the GLCM matrix. Four GLCM matrixes have to be generated based on the four GLCM directions: 0º, 45 º, 90 º and 135 º as shown in Figure 8.

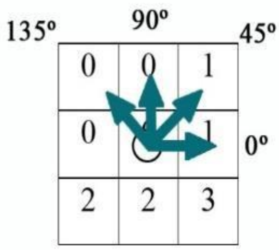


Figure 4. GLCM directions

If p(i,j) is the $(i,j)^{th}$ entry in a normalized GLCM matrix, N_g is the number of distinct gray levels in the quantized image, then GLCM features can be calculated as follows: a. Angular Second Moment Angular second moment or energy is a measure of textural uniformity of an image.

$$ASM = \sum_i \sum_j \{p(i,j)\}^2 \quad (8)$$

b. Contrast

Contrast is a difference moment of the P matrix and is a measure of the contrast or the amount of local variations present in an image.

$$Contrast = \sum_{n=0}^{Ng-1} n^2 \left\{ \sum_{i=1}^{Ng} \sum_{\substack{j=1 \\ |i-j|=n}}^{Ng} p(i,j) \right\} \quad (9)$$

c. Inverse Difference Moment (IDM)

Inverse difference moment measures homogeneity. This parameter achieves its largest value when most of the occurrences in GLCM are concentrated near the main diagonal.

$$IDM = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$$

(10) d. Entropy

Entropy measures the disorder of an image and it achieves its largest value when all elements in P matrix are equal.

$$Entropy = - \sum_i \sum_j p(i,j) \log (p(i,j)) \quad (11)$$

e. Correlation

Correlation feature is a measure of gray-tone linear-dependencies in the image.

$$Correlation = \sum_{i,j=0}^{N-1} P(i,j) \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (12)$$

with

$\mu = \sum^{N}{}_{i,j=0}{}^{-1} iP(i,j)$ (13) $\sigma = \sum^{N}{}_{i,j=0}{}^{-1} P(i,j)(i-\mu)^2$ (14)

2.5. Classification using Support Vector Machine

Support Vector Machine (SVM) method tries to find the best hyperplane that separates two classes in an input space [14]. Figure 7 shows some patterns that belong to class +1 and -1 separated by a hyperplane.

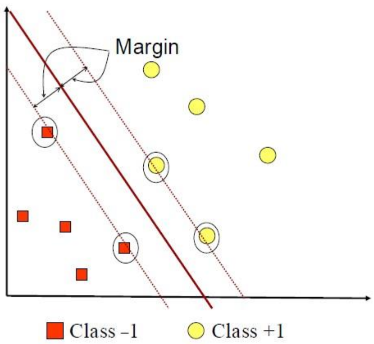


Figure 5. Hyperplane

For a linearly separable data, the following function is used to separate each class.

$$f(x) = w^T x + b = 0 \quad (15)$$

As for the case where the classes are not separable, the following function is used.

$$w^T x + b = \pm 1 \quad (16)$$

3. Experimental Results and Discussion

The testing is conducted several times to find out the effect of some parameters on the classification result. These parameters are the number of classes, image resolution, and rotation.

3.1. The effect of the number of classes on accuracy

The first testing was conducted by classifying the testing data into 3 classes with multi-class SVM. These classes are fresh, half-fresh, and defective beef. The testing was conducted 5 times by using 5 different features. The second testing was conducted using 2 classes SVM with the same scenario as the first testing. Table 2 shows the testing results for both 3 and 2 classes classification. The image resolution used in this testing is 256x256 pixel.

Table 3. The effect of the number of classes on accuracy

Datasets	Number of classes	Accuracy				
		HSI	YCbCr	GLCM	HSI + GLCM	YCbCr + GLCM
CB	3	**83.00%**	63.00%	45.00%	47.00%	45.00%
RT	3	63.00%	60.00%	37.00%	43.00%	48.00%
Average		**74.00%**	**59.20%**	**41.00%**	**45.00%**	**46.50%**
CB	2	**95.00%**	80.00%	73.00%	**93.00%**	80.00%
RT	2	73.00%	77.00%	78.00%	88.00%	77.00%
Average		**84.00%**	**78.50%**	**75.50%**	**90.50%**	**78.50%**

Note: CB = Cold Beef / Beef in Refrigerator, RT = Room Temperature

As shown in Table 2, the classification using 2 classes obtained a significantly higher accuracy than the 3 classes classification. The highest accuracy of 3 classes classification is 83% using HSI features on the cold beef dataset while the lowest is 37% using GLCM features on the room temperature dataset. Meanwhile, the highest accuracy for 2 classes classification is 95% using HSI features on the cold beef dataset and the lowest is 73% using GLCM features on the cold beef dataset and HSI features on the room temperature dataset.

The accuracy of the room temperature dataset is noticeably lower than the cold beef dataset in all cases. In the 2 class classification, the accuracy of the room temperature dataset using HSI, YCbCr, and GLCM feature is under 80% but the accuracy is improving to 88% when HSI and GLCM are combined. This improvement gives a better average accuracy for HSI+GLCM feature.

The highest average accuracy for 3 classes classification is obtained by using the HSI feature with the accuracy of 74% while the highest average accuracy for 2 classes classification is obtained by using HSI+GLCM with the accuracy of 90.5%. The accuracy improvement from 3 classes classification to 2 classes classification is caused by the SVM classifier which is originally a 2-classes classifier.

3.2. The effect of the image resolution on accuracy

We also conducted the classification to find out the effect of the image resolution to the accuracy. We used 128x128 pixel and 512x512 pixel images and compare them with the previous result which used 256x256 pixel images. For this classification, we used the 2-classes classification. The result is given in Table 3.

Table 4. The effect of the image resolution on accuracy

Datasets	Image resolution	Accuracy (%)				
		HSI	YCbCr	GLCM	HSI + GLCM	YCbCr + GLCM
CB	128	**93.00%**	77.00%	73.00%	**93.00%**	57.00%
RT	128	72.00%	75%	73.00%	82.00%	78.00%
Average		**82.50%**	**76.00%**	**73.00%**	**87.50%**	**67.50%**
CB	256	95.00%	80.00%	73.00%	93.00%	80.00%
RT	256	73.00%	77.00%	78.00%	88.00%	77.00%

Average		**84.00%**	**78.50%**	**75.50%**	**90.50%**	**78.50%**
CB	512	**97.00%**	78.00%	52.00%	93.00%	87.00%
RT	512	75.00%	77.00%	77.00%	85.00%	83.00%
Average		**86.00%**	**77.50%**	**64.50%**	**89.00%**	**85.00%**

Note: CB = Cold Beef / Beef in Refrigerator, RT = Room Temperature

Table 3 shows that in most cases, the image resolution does not give a significant effect on the accuracy. The accuracy of some features change, either increasing or decreasing, but this change only ranges from 1-3%. Two features that change significantly are GLCM and YCbCr+GLCM. The accuracy of GLCM decreased to 21% from 256x256 pixel to 512x512 pixel. On the other hand, the accuracy of YCbCr+GLCM increased to 23% from 128x128 pixel to 256x256 pixel. Two features that constantly increases along with the increasing of the image resolution are HSI and YCbCr+GLCM features.

Image resolution also affects the computation time. Although a higher resolution gives a better performance on some feature, the computation time of the higher resolution image is also higher. It takes a lot of time to compute a high-resolution image. Table 4 shows the computation time comparison for 1 image of all image resolution.

Table 5. The effect of the image resolution on computation time in second

Image resolution	HSI	YCbCr	GLCM	HSI+ GLCM	YCbCr+ GLCM
128x128	0.60	0.64	5.53	5.72	5.46
256x256	1.96	1.81	6.93	7.48	7.23
512x512	8.25	6.62	10.97	17.62	16.97

The system takes a relatively short time to compute 1 image with the resolution of 128x128 pixel and 256x256 pixel. The computation time increases significantly when the image resolution is 512x612 pixel.

Based on the testing result, it is known that the increase of image resolution gives a positive effect on the accuracy of HSI and YCbCr+GLCM features. Meanwhile, the YCbCr, GLCM and HSI+GLCM features accuracy do not change constantly when the resolution is increased or reduced. The image resolution also affects the computation time. Therefore, the best image resolution in this testing is 256x256 pixel in terms of accuracy and computation time.

3.3. The effect of rotation on the accuracy

This testing is done to find out the rotation effect on the accuracy. The classification is conducted by rotating the test images to 90ºCW and 180ºCW and compare the result with the normal image. This testing is carried out with 2-classes classification. Table 6 shows the classification result.

Table 6. The effect of image rotation on accuracy

Datasets	Rotation	Accuracy (%)				
		HSI	YCbCr	GLCM	HSI+ GLCM	YCbCr+ GLCM
CB	0º	**95.00%**	80.00%	73.00%	93.00%	80.00%
RT	0º	73.00%	77.00%	78.00%	88.00%	77.00%
Average		**84.00%**	**78.50%**	**75.50%**	**90.50%**	**78.00%**
CB	90ºCW	**95.00%**	82.00%	72.00%	**95.00%**	87.00%
RT	90ºCW	72.00%	75.00%	82.00%	83.00%	78.00%
Average		**83.50%**	**78.50%**	**77.00%**	**80.00%**	**82.50%**

CB	180ºCW	92.00%	82.00%	72.00%	**97.00%**	85.00%
RT	180ºCW	72.00%	75.00%	77.00%	83.00%	82.00%
Average		**82.00%**	**78.50%**	**74.50%**	**90.00%**	**83.50%**

Note: CB = Cold Beef / Beef in Refrigerator, RT = Room Temperature

The result shows that the 90ºCW and 180ºCW rotation does not give a big difference to the accuracy. The difference only ranges from 1-5% either for the increasing or decreasing of accuracy. This means that even with the rotation of 90ºCW and 180ºCW, the testing image still can be recognized well.

3.4. Analysis of Features

Analysis of features is done by generating the distribution of feature values to find out the best features from each method. In this case, the best features are the features that have a significant difference between the fresh and defective categories. Three features are analyzed, HSI, YCbCr, and GLCM features. The feature distribution is generated by computing the average feature values of all training data.

3.4.1. Analysis of HSI Features

HSI color feature consists of 12 statistical features from each layer of HSI color space. Figure 6 and Figure 7 are the graphs of the average feature values of all training data on both cold beef and room temperature datasets.

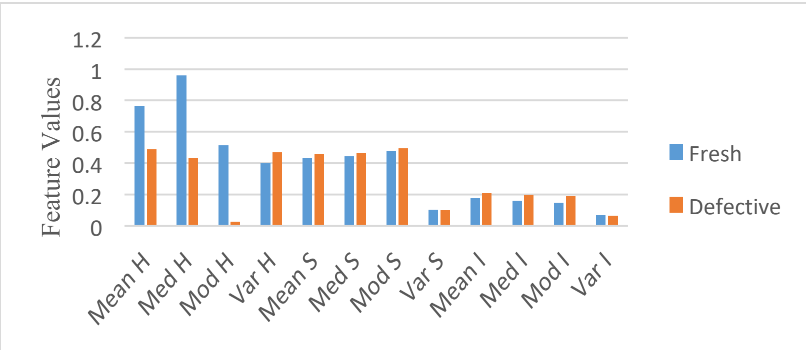


Figure 6. Distribution of feature values of the cold beef dataset on HSI color space

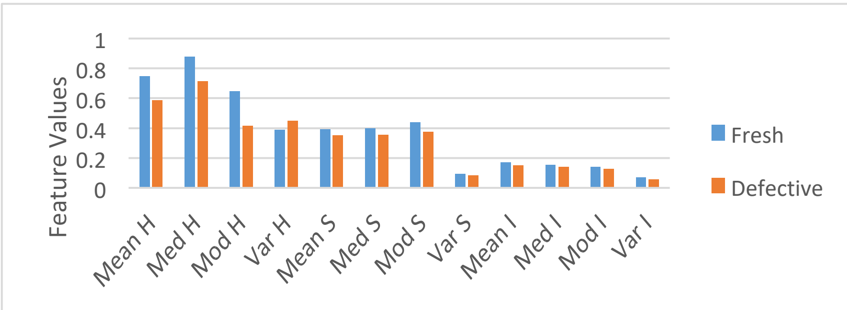


Figure 7. Distribution of feature values of room temperature beef dataset on HSI color space

As shown in Figure 6, and Figure 7, for both datasets on HSI color space, the feature that has a significant difference between fresh and defective categories are the statistical features of H layer. As for the S and I layers, the fresh and defective categories are not clearly separated.

3.4.2. Analysis of YCbCr Features

YCbCr color feature also consists of 12 statistical features from each layer of YCbCr color space. Figure 8 and Figure 9 are the graphs of the average feature values of all training data on both cold beef and room temperature datasets.

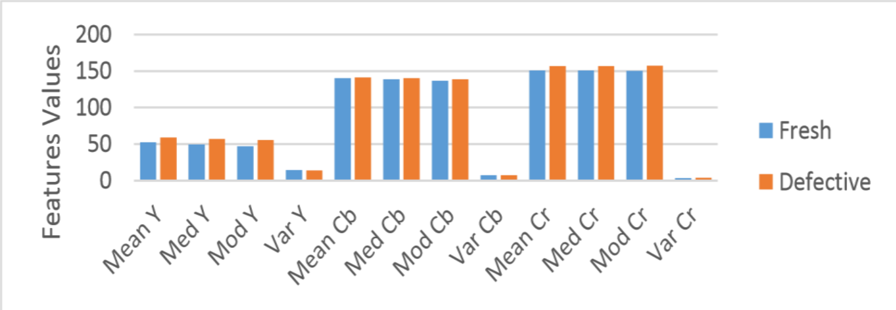


Figure 8. Distribution of feature values of the cold beef dataset on YCbCr color space

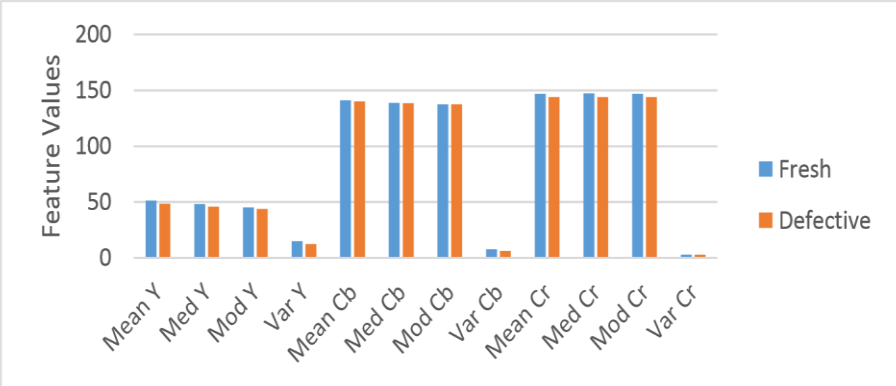


Figure 9. Distribution of feature values of room temperature beef dataset on YCbCr color space

Unlike the HSI color feature, YCbCr color feature does not have a significant difference between the fresh and defective categories for both datasets. One layer that has a slightly noticeable difference is the Y layer but not as significant as the H layer of HSI color space.

3.4.3. Analysis of GLCM Features

GLCM textural feature consists of 20 features which are generated from the 4 GLCM directions. Figure 10 and Figure 11 are the graphs of the average feature values of all training data on both cold beef and room temperature datasets.

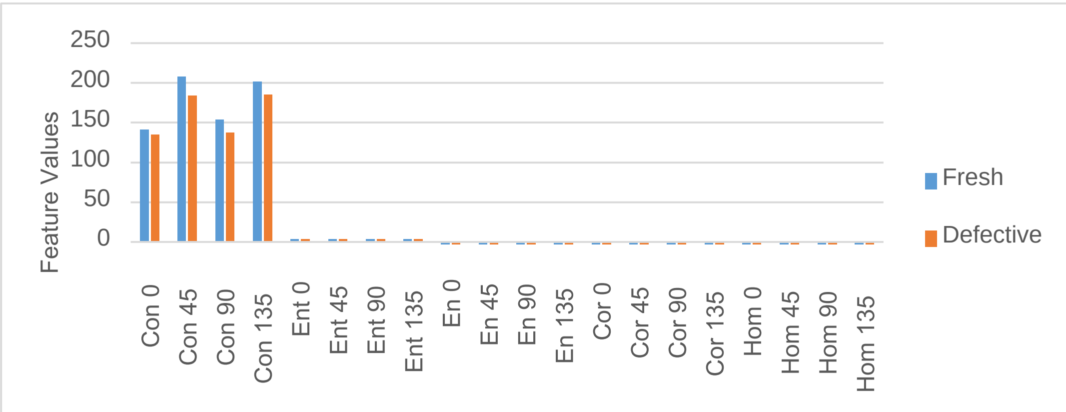


Figure 10. Distribution of feature values of the cold beef dataset on GLCM textural features

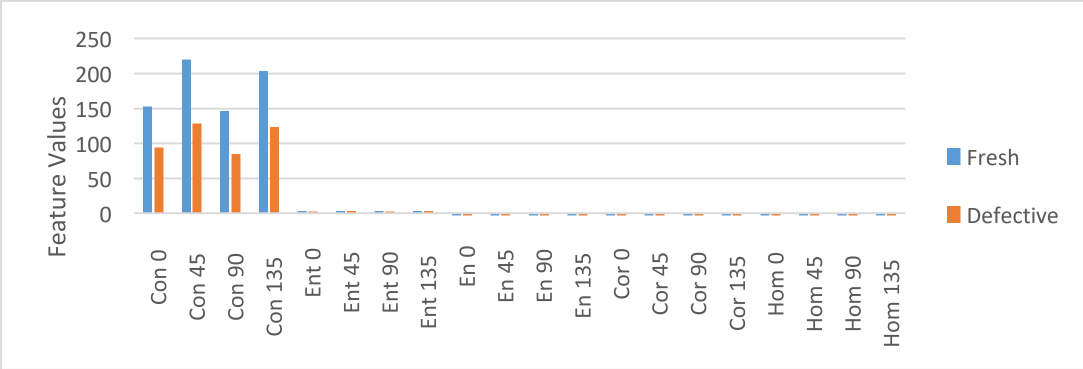


Figure 11. Distribution of feature values of room temperature beef dataset on GLCM textural features

The room temperature beef dataset has a better feature distribution than the cold beef dataset. The difference between fresh and defective categories for the room temperature dataset have a significant difference on the contrast features. The cold beef dataset also has a clear difference between fresh and defective beef datasets but not as significant as the room temperature beef dataset. This causes the room temperature beef dataset to have a better accuracy than the cold beef dataset.

4. Implementation

This system has been implemented in the android device so it can be used widely by the beef consumers in order to identify the beef quality. The feature used in this application is HSI+GLCM with 2 class classification since it obtained the best average accuracy for both datasets during the testing process. The image size used is 256x256 pixel because it does not take a long time to be processed yet obtains a high accuracy compared to the other resolutions. The device used is a smartphone with the specification given in Table 7.

Table 7. Device specification

OS	Android 6.0.1 (Marshmellow)
CPU	1.2GHz Quad Core
RAM	1.5GB
Primary Camera	13MP
Secondary Camera	5MP
Display resolution	720x1280 pixel

The application has been working properly on the android device. The input image can be taken directly from the camera and also can be loaded from the device's storage. Figure 12 (a) to (d) shows the application interface on and android device.

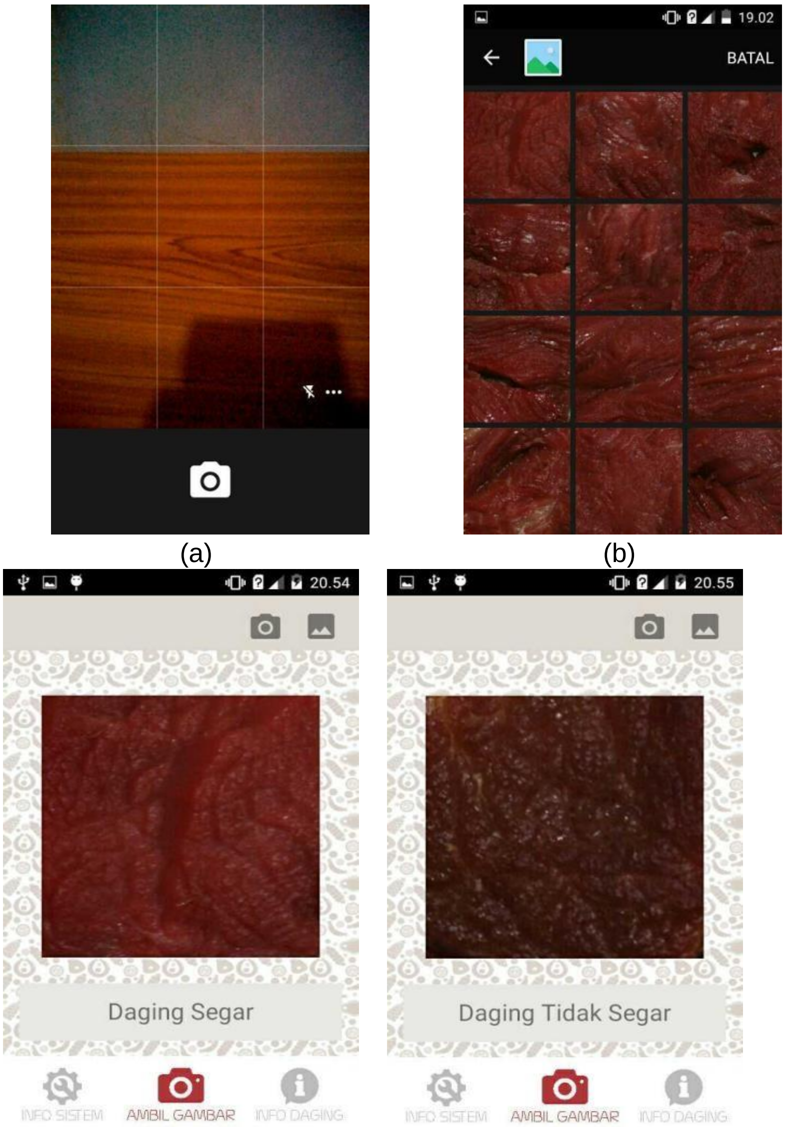


Figure 12. The user interface of the application, (a) Camera, (b) Gallery, (c) Conclusion for the fresh beef, (d) Conclusion for the defective beef.

5. Conclusion

Beef quality classification based on color and texture feature using SVM showed various results over different features. From the testing results, it can be concluded that the system showed a better performance in the 2-classes classification. The highest accuracy obtained using the 512x512 pixel image on the HSI feature. The best average accuracy was 90.5% obtained using HSI+GLCM feature with the image resolution of 256x256 pixel. Image resolution affects the computation time, a larger resolution takes a longer computation time. The rotated image (90ºCW and 180ºCW) does not give a significant difference to the accuracy, the beef quality still can be recognized well in this rotation. Color and texture features can be used to classify the beef quality.

7. Future Works

The following can be considered for the future works:

1. This method can be used to classify other types of meat.
2. Only use the features that have a significant difference between fresh and defective categories.

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