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Combination of extraction features based on texture and colour feature for beef and pork classification

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Abstract. Behaviour of traders mixing beef and pork is very detrimental to consumers, especially followers of Islam because it is related to legal or forbidden food. So, consumers must be protected from these rogue traders. However, differentiating beef and pork is not easy for ordinary people, especially if you only see from one information that is the colour or texture. In this paper, we proposed a new combination of extraction features based on texture and colour features for the classification of beef and pork. The feature of the texture is to see the local information optimally by using a local optimal-oriented pattern (LOOP) so that it can provide better texture information. The colour features that will be used are hue, saturation, and value (HSV). Texture and colour features are combined into one, so that more enrich the information used. The combination of optimal local-oriented pattern features and hue saturation value gives increased accuracy for the classification of pork and beef. The results of tests that have been done show that the success rate of calcification by using a combination of features has increased. accuracy obtained is equal to 99.16 percent, recall 100 percent and precision 98.36 percent. this shows that by utilizing the colour features and texture features can provide improved classification due to increased information that can be used to do the classification.

1. Introduction

Beef is a food that has a high protein content. Beef is not only consumed by households, but beef is also used in industry, hotels, and restaurants. Every year the need for beef continues to increase in Indonesia [1]. Traders generally sell meat based on its type, such as chicken, beef, mutton, and pork. But naughty traders who want to get high profits do a mixture of beef and pork [2]. According to experts from IPB, beef and pork can be distinguished by observing directly one by one, but this can only be done by experts [3] . Beef and pork that are not easily distinguished for ordinary people are used by the sellers. Behaviour of traders like this is very detrimental to consumers, especially the adherents of Islam because it is related to legal or forbidden food [4]. Consumers need to be given protection from such traders, so technology is needed to differentiate between beef and pork by utilizing image processing technology.

The process of distinguishing between beef and pork can utilize image processing and machine learning, namely by doing classification. The application image processing for example [1], [5], [6], [7], and [8]. Image processing there are several steps that can be done to determine the characteristics of an image which includes pre-processing, segmentation, filtering, feature extraction, and others. The process of classifying pork and beef can be seen by utilizing the colour features and texture features in the image.

Therefore, in this paper combines colour extraction features and texture features for the classification of pork and pork.

Research [9], [10] distinguishes between beef and pork using the grey level co-occurrence matrix (GLCM) method. Where researchers only utilize the texture features of the meat, so it does not get maximum success. Research [11], [6], [3], and [12] distinguish between beef and pork by utilizing hue, saturation, and value (HSV) features and grey level co-occurrence matrix features. The research did not use local texture information optimally.

In this paper, we proposed a new combination of extraction features based on texture and colour features for the classification of beef and pork. The feature of the texture is seen optimal local information by using local optimal oriented patterns (LOOP) so that it can provide better texture information. The colour features to be used are hue, saturation, and value. The combined texture and colour features together, so that it can provide a high degree of classification accuracy. The code is available on GitHub (https://github.com/arifmudi/Combination-Of-Extraction-Features-Based-On-Texture-and-Colour-Feature-for-Beef-and-Pork-Classificat).

2. Methodology

In this study data were obtained from traditional markets in Pekanbaru. The location of this market is bottom's market and cipuan's market. The amount of data used is as much as 400 data. The process of taking images using a DSLR Canon EOS Kiss X50 with ISO between 100 to 200. The distance of the image capture between the camera and the object is 15 cm.

In this study a new combination of extraction methods is proposed to classify pork and beef. The extraction method used is based on the texture and colour of the image. method of image extraction based on features, namely local optimal-oriented pattern (LOOP). Local optimal-oriented pattern method is used to obtain optimal local information in the image so that it gives better texture information. Feature extraction methods based on the colours used are Hue, Saturation, and value (HSV). This method of hue, saturation and value is able to provide information from the colour of the image as seen in humans, so the proposed method by optimally combining local information (LOOP) and image colour using HSV will provide a better success rate. after the image extraction process, the classification process is then carried out using the support vector machine method.

2.1 local optimal-oriented pattern

Local optimal-oriented patterns execute rotating invariants into the main formulation of local binary descriptors, thus overcoming the weaknesses of the most existing genre descriptors. In the process we reduce complex processing time and improve classification. Besides that, using optimal locally oriented patterns will increase local information obtained from the texture features in the image.

Each image has texture characteristics, so by using Local optimal-oriented patterns will be able to get the texture features of the image being processed [13]. Local optimal-oriented patterns process uses Equation 1.

$$LOOP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c).\, 2^{wn} \quad (1)$$

Where

$$s(x) = \begin{cases} 1, & if\ x \geq 1 \\ 0, & otherwise. \end{cases} \quad (2)$$

LOOP (x_c, y_c) is a pixel point that will find its value using LOOP and in neighbours pixels (n = 0, 1, ..., 7) becomes the pixel intensity in a 3x3 environment (x_c, y_c) excluding the middle pixel i_c.

2.2 Hue, Saturation, and value

HSV is a model derived from the RGB colour model where HSV can be seen by looking along the black and white diagonal. Hue is the turning angle around the upright axis where red is at 0^0 and yellow at 60^0. Saturation is between 0 and 1. Expressed as the ratio between the purity of the selected colour and its maximum colour purity (S = 1). S = 0 means Gray, S = 1 means pure. Value is between 0 (black) and 1 (white). To get the value from HSV, first convert the RGB image into HSV, using equation 3 to equation 9.

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

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

$$b = \frac{b}{R+G+B} \tag{5}$$

$$V = max(r, g, b) \tag{6}$$

$$S = \begin{cases} 0, & if\ V = 0 \\ 1 - \frac{min(r,g,b)}{v}, & if\ V > 0 \end{cases} \tag{7}$$

$$H = \begin{cases} 0, & if\ S = 0 \\ \frac{60*(g-b)}{S*V}, & if\ V = r \\ 60 * \left[2 + \frac{b-r}{S*V}\right], & if\ V = g \\ 60 * \left[4 + \frac{r-g}{S*V}\right], & if\ V = b \end{cases} \tag{8}$$

$$H = H + 360, if\ H < 0 \tag{9}$$

2.3 Support Vector Machine

Support vector machine (SVM) is one technique for making predictions, both classification and regression cases [14]. In this technique, the separator function (classifier / hyperplane is the best among an infinite number of functions to separate two types of objects. The best hyperplane is a hyperplane located in the middle between two sets of objects from two classes. The best hyperplane is called the optimal hyperplane. support vector machine is explained in detail by El-naqa [15].

After getting the feature results from extraction using LOOP and HSV. then the classification is done using the Support vector machine. The classification process is carried out with 3 scenarios: classification using the LOOP feature, classification using the HSV feature and Classification by combining the LOOP-HSV features.

2.4 Performance evaluation

The performance evaluation of the proposed method uses matrix convolution with accuracy, recall, and precision techniques. This technique is used to calculate quantitatively. Accuracy is calculating the success rate of nature doing calcifications. Recall is the number of relevant documents found in the prediction results. Precision is the number of relevant tweets obtained from the total number of detected results [16]. The performance evaluation uses Equation 10, Equation 11, and Equation 12.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{10}$$

$$Recall = \frac{TP}{TP+FN} \tag{11}$$

$$Precision = \frac{TP}{TP+FP} \tag{12}$$

3. Result and Discussion

The distribution of training data and test data used is 70 percent, 80 percent, and 90 percent. Distribution of 70 percent is training 280 images and testing 120 images. Distribution of 80 percent is training 320 images and testing 80 images. Distribution of 90 percent is training 360 image and testing 40 images. The first scenario is the classification of pork and beef using features of hue, saturation, and value (HSV). The second scenario is the classification of pork and beef using local-oriented pattern (LOOP) features. The third scenario is the classification of pork and beef using a combination of HSV and loop features.

Table 1. Result Classification with feature Hue, Saturation, and value. 70 percent image distribution.

	Pork	Beef
Pork	58	2
Beef	2	58

Table 1 is a classification using distribution of training data images 70 percent and testing data 30 percent. The first scenario Table 1 succeeded in classifying pork and beef with an accuracy of 96.67 percent, recall 96.67 percent and Precision 96.67 percent. the results show that by using the hue, saturation, and value colour space features have been able to classify pork and beef. and there was a class in doing classification. classification using hue, saturation, and value still needs to be added with other features.

Table 2. Result Classification with feature Local optimal-oriented Pattern. 70 percent image distribution.

	Pork	Beef
Pork	41	19
Beef	13	47

Table 2 is a classification using distribution of training data images 70 percent and testing data 30 percent. The second scenario in Table 2 succeeded in classifying pork and beef with an accuracy of 73.33 percent, recall 68.33 percent and Precision 75.93 percent. The results show that by using the Local texture feature, optimal-oriented pattern is still low in the success of classification. This result is because the texture of the meat is still quite difficult to detect by using this feature extraction. however, precision by using local optimal-oriented pattern is quite good. thus, this optimal local-oriented pattern can be combined with the colour space method to increase success in detecting pork and beef.

Table 3. Result Classification with feature Combination HSV and LOOP. 70 percent image distribution.

	Pork	Beef
Pork	60	0
Beef	1	59

Table 3 is a classification using distribution of training data images 70 percent and testing data 30 percent. Third scenario Table 3 succeeded in classifying pork and beef with an accuracy of 99.17 percent, recall 100 percent and Precision 98.36 percent. The results show that by combining the optimal local texture-oriented pattern features and colour space features the hue, saturation, and value. It can increase the success in the classification of pork and beef. These results indicate that in classification using more than one side of the feature will increase the success of both recall, accuracy, and precision.

Table 4. Result Classification with feature Hue, Saturation, and value. 80 percent image distribution.

	Pork	Beef
Pork	39	1
Beef	0	40

Table 4 is the first scenario with the addition of training data. Table 4 classifications using image distribution of training data 80 percent and testing data 20 percent. The first scenario Table 4 succeeded in classifying pork and beef with an accuracy of 98.75 percent, recall 97.5 percent and Precision 97.5 percent. The results show that increasing the amount of training in the colour space hue, saturation, and value features has been able to classify pork and beef more and better than before. however, classification by relying on colour space hue, saturation, and value is still wrong in detecting beef. this is very dangerous for consumers because they would think the meat is beef, but it turns out pork.

Table 5. Result Classification with feature Local optimal-oriented Pattern. 80 percent image distribution.

	Pork	Beef
Pork	26	14
Beef	12	28

Table 5 is the second scenario with the addition of training data. Table 5 classifications using image distribution of training data 80 percent and testing data 20 percent. The second scenario in Table 5 succeeded in classifying pork and beef with an accuracy of 67.5 percent, recall 65 percent and Precision 68.4 percent. The results show that increasing the amount of training in the optimal local feature-oriented pattern does not greatly affect the success or precision it gets. this shows that in using local features the optimal-oriented pattern really requires additional information to do the classification.

Table 6. Result Classification with feature Combination HSV and LOOP. 80 percent image distribution

	Pork	Beef
Pork	60	0
Beef	1	59

Table 6 is the third scenario which is done by increasing the amount of training data. Table 6 classification uses image distribution of training data 80 percent and testing data 20 percent. Third scenario Table 6 succeeds in classifying pork and beef with accuracy 100 percent, recall 100 percent and precision 100 percent. The results show that by increasing the amount of training data and the process of combining optimal local texture-oriented pattern features and colour space features hue, saturation, and value. this can increase success in the classification of pork and beef. therefore, training data are needed in large numbers to be able to enrich information on differences between pork and beef.

Table 7. Result Classification with feature Hue, Saturation, and value. 90 percent image distribution.

	Pork	Beef
Pork	20	0
Beef	0	20

Table 7 is the first scenario with the addition of training data and reduction of testing data. Test data used is data that is difficult to classify. Table 7 classification uses image distribution of training data 90 percent and testing data 10 percent. The first scenario in Table 7 succeeded in classifying pork and beef with accuracy 100 percent, recall 100 percent and Precision 100 percent. The results showed that the increasing amount of training in the colour features space hue, saturation, and value was able to classify pork and beef better than before.

Table 8. Result Classification with feature Local optimal-oriented Pattern. 90 percent image distribution.

	Pork	Beef
Pork	11	9
Beef	6	14

Table 8 is the second scenario with the addition of training data and reduction of testing data. Test data used is data that is difficult to classify. Table 8 classifications use the image distribution of training data 90 percent and test data 10 percent. The second scenario in Table 8 succeeded in classifying pork and beef with an accuracy of 62.5 percent, recall 55 percent and Precision 64.7 percent. The results showed that the increasing number of training in local optimal-oriented pattern features was not able to increase success in classifying pork and beef. this further reinforces that optimal feature-oriented local features require other feature information such as colour space features.

Table 9. Result Classification with feature Combination HSV and LOOP. 90 percent image distribution.

	Pork	Beef
Pork	20	0
Beef	0	20

Table 9 is the third scenario with the addition of training data and reduction of testing data. Test data used is data that is difficult to classify. Table 9 classification uses image distribution of training data 90 percent and testing data 10 percent. Third scenario Table 9 succeeds in classifying pork and beef with accuracy 100 percent, recall 100 percent and Precision 100 percent. The results showed that increasing the amount of training that was getting bigger and combined local optimal-oriented pattern features and colour space features of hue, saturation, and value were able to increase success in classifying pork and beef. this further reinforces that by combining optimal local-oriented pattern features and colour space hue, saturation, and value can improve success in classifying pork and beef. classification by combining features some of this information is very forming in an accurate classification.

Based on the results of the first scenario, there are still some failures in classifying pork. This is because there are some images that are difficult to observe if only with colour. So, if only using colour will cause errors in calcifying pork. The result of the second scenario shows that the success rate to do the calcification by using information rotation of the feature information of the text is still not very helpful. This can be seen from the number of images that failed to do the classification. The third scenario for 70 percent distribution image, method proposed by combining features between colour features and texture features can improve the ability to classify pork and beef compared to using only one feature such as HSV or LOOP. Improved accuracy of the proposed method for the HSV method is 2.49 percent and for the LOOP method is 25.83. This shows that combining features can provide an increase in the success of classification.

4. Conclusion

This study proposes a new combination of extraction features based on texture and colour for the classification of pork and beef. The colour features used are hue, saturation, and value (HSV). The texture feature used is the Local optimal-oriented pattern (LOOP). Based on the results of tests that have been done show that the success rate of calcification by using a combination of features has increased. The distribution of 70 percent, accuracy obtained is equal to 99.16 percent, recall 100 percent and precision 98.36 percent. The distribution of 80 percent, accuracy obtained is equal to 100 percent, recall 100 percent and precision 100 percent. The distribution of 90 percent, accuracy obtained is equal to 100 percent, recall 100 percent and precision 100 percent. This shows that by utilizing the colour features and texture features can provide improved classification due to increased information that can be used to do the classification.

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