Accredited Ranking SINTA 2
Decree of the Director General of Higher Education, Research, and Technology, No. 158/E/KPT/2021
Validity period from Volume 5 Number 2 of 2021 to Volume 10 Number 1 of 2026

Published online on: **http://jurnal.iaii.or.id**

JURNAL RESTI
(Rekayasa Sistem dan Teknologi Informasi)
Vol. 6 No. 3 (2022) 421 - 429 ISSN Media Electronic: 2580-0760

Fuzzy Learning Vector Quantization for Classification of Mixed Meat Image Based on Character of Color and Texture

Lidya Ningsih[1], Agus Buono[2], Mushthofa[3], Toto Haryanto[4]
[1,2,3,4]Ilmu Komputer, Fakultas Matematika Ilmu Pengetahuan Alam, Institut Pertanian Bogor
[1]lidyaningsih@apps.ipb.ac.id, [2]agusbuono@apps.ipb.ac.id, [3]mush@apps.ipb.ac.id, [4]totoharyanto@apps.ipb.ac.id

Abstract

Beef consumption is quite high and expensive in the world. In Indonesia, beef prices are relatively expensive because the meat supply chain from farmers to the market is quite long. The high demand for beef and the difficulty of obtaining meat are factors in the high price of meat. This makes some meat traders cheat by mixing beef and pork (oplosan). Mixing beef and pork is detrimental to beef consumers, especially those who are Muslim. In this paper, we proposed a new strategy for identifying beef, pig, and mixed meat utilizing Fuzzy learning vector quantization (FLVQ) Based on the color and texture aspects of the meat. The HSV (Hue saturation value) approach is used for color features, whereas the GLCM (Gray level co-occurrence matrix) method is used for texture features. This study makes use of primary data collected from the Pasar Bawah Tourism and Cipuan *Market in* Pekanbaru, Riau *Province. The data set consists of 600 photos, 200 each of beef, pork, and mixed. Based on the test scenario, the coefficient of fuzzyness and learning rate affect the accuracy of meat image identification. The proposed strategy has succeeded in classifying pork, beef and mixed meat with the best percentage of accuracy results in theclasses of beef and pork, beef and mixed, pork and mixed meat, respectively, at 100%, 97.5%, and 95%. This demonstrates that the proposed strategy has succeeded in classifying the image of pork, beef, and mixed.*

Keywords: Pork, Beef, FLVQ, GLCM, HSV, Image Processing

1. Introduction

Meat is an important food element in addressing nutritional demands since it contains high-quality protein and full amino acids [1]. Meat comes in many varieties, including beef, pork, mutton, poultry, and so on [2]. Beef is consumed more frequently because it is high in nutrients and animal protein, as well as is easy to cook [3].

Beef consumption is very high over the world, owing to high meat prices. Because of the length of the meat supply chain from farmers to the market, beef is relatively expensive in Indonesia [4]. According to the Head of the Riau Province Livestock Service Office, the demand for beef is roughly 100 heads per day, with a % surge before the religious holiday [5]. The high demand and the difficulty of getting beef sometimes make the price of the meat expensive [1] with an increase that occurs every year [5]. This situation causes losses for beef traders, prompting some to conduct fraud by combining beef with pork (mixed). The pork was chosen as a beef mixture because the price of pork is cheaper with the color and texture of pork which is almost the same as beef [3].

This incidence of mixing beef with pork is extremely harmful to meat-eaters, particularly Muslims [6]. Muslims are advised to eat permissible and healthy foods (Surah Al-Baqarah: 172, Al-Maidah: 4). Muslims are prohibited from eating haram food by Allah SWT. Pork (Surah Al-Baqarah: 173, Al-Maidah: 3, Al-An'am: 145) is one among the banned foods. Physical (tenderness, smell, and taste), visual (meat color and texture), chemical (compounds), and biological (microorganisms) methods can all be used to distinguish beef from pork [7]. Pork is paler than beef in color. Meanwhile, beef fiber is more evident than pig fiber in terms of texture [2]. One way that can be used to recognize beef and pork in the field of informatics is to use digital image techniques considering that digital image processing can create a computerized meat recognition system that can distinguish beef and pork like humans [8].

Color and texture qualities are used to do research on beef and pork in the field of digital imaging. According

Accepted: 09-05-2022 | Received in revised: 17-06-2022 | Published: 30-06-2022

to a study [9] that examined Hue saturation intensity (HSI) and hue saturation value (HSV) color features in detecting rose withering, HSV color features performed better. The textural features GLCM, LBP, LBGLCM, GLRLM, and SFTA were compared in a study conducted by [10]. The GLCM algorithm produces excellent results, with the highest GLCM percentage of 92.8%.

The accuracy of K-Means clustering in beef and pork research conducted by [11] was 65%. However, the accuracy gained in this study is rather low because it only employs 100 data points from two varieties of meat, pork, and beef, and data sampling is done without respect for data acquisition. This has the potential to be negative in determining the identification findings because the picture data obtained may not be as clear as it could be if the distance of data collecting is not taken into account.

Paper [3] used the LVQ algorithm based on HSV color features and GLCM texture features to show the difference between pork and beef, obtaining an accuracy of 76.25%. The LVQ algorithm can realize alternative neural networks because the neurons in LVQ learning are non-linear, and do not take much time to converge [12]. Unfortunately, the LVQ algorithm has several flaws, including the fact that the weight vectors may not converge during the training process, and that each attribute dimension's contribution to the classification is equal, resulting in information from each attribute dimension in the input sample not being fully utilized [12].

In this paper, we proposed a new strategy for identifying beef, pig, and mixed meat utilizing Fuzzy learning vector quantization (FLVQ) Based on the color and texture aspects of the meat. The HSV approach is used for color features, whereas the GLCM method is used for texture features. The proposed is hoped to be able to classify beef, pig, and mixed meat, reducing the problem of mixing beef with pork and producing better results than prior experiments.

2. Research Methods

This study proposes a new strategy for classifying beef, pork, and mixed meat using Fuzzy learning vector quantization (FLVQ) based on the color and texture features of the meat. The classification process consists of training and testing processes. The training process is used to build a model from image data, while the testing process is used to see the success rate of the model built.

The stages in this research consisted of data acquisition, preprocessing, feature extraction, modeling, and evaluation. Preprocessing was done to prepare image data by removing the background and uniforming the pixel size of the image. In this study, the pre-processing stage was carried out, namely cropping and resizing.

Feature extraction in this study was performed by using the Hue saturation value (HSV) color feature and the Gray level co-occurrence matrix (GLCM) texture feature to obtain the required features of an image. The value of these features was utilized as input in the classification (modeling) process. In this study, the classification procedure is carried out using machine learning techniques and the Fuzzy learning vector quantization (FLVQ) algorithm. This study's findings will be compared to previous research. [3].

2.1 Image Data

Figure 1. Types of Meat Image

The data utilized in this study were acquired from the Pasar Bawah Market and Pasar Cipuan Pekanbaru City, Riau Province, and comprised of three categories of images: beef, pork, and mixed meat (Figure 1). The data on beef, pork, and mixed meat images was gathered using image acquisition.

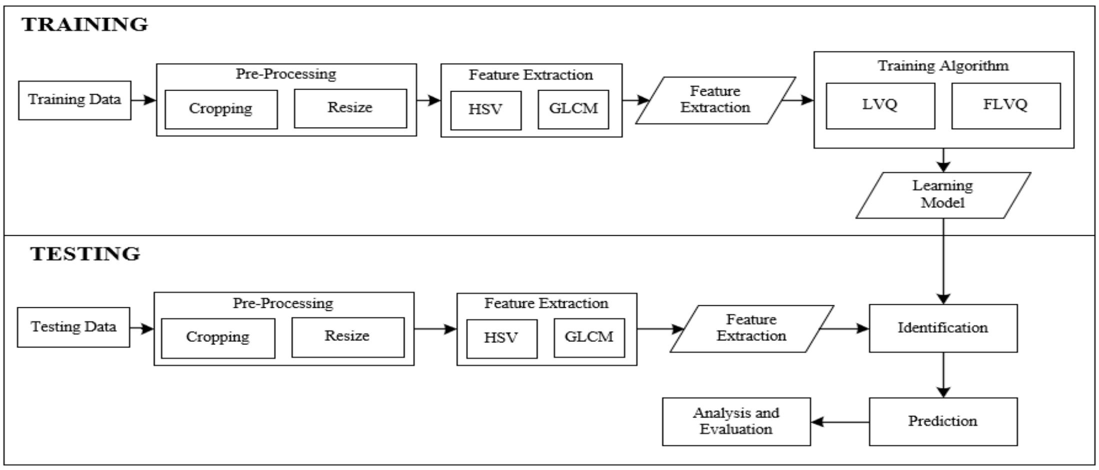

Figure 2 Research Stages of Meat Image Identification

DOI: https://doi.org/10.29207/resti.v6i3.4067

The image in this investigation were captured with a Canon EOS KISS X50 DSLR camera set to ISO 100 to 200 and a distance of 5 to 15cm between the camera and the object. The retrieval of image data takes place during the day, without the use of any additional lighting.

Image data retrieval was performed by using a white background by positioning the image object in the middle. The images used are the image of beef, the image of pork, and the image of mixed meat. The image of mixed meat is done by placing pieces of beef and pork side by side. The percentage of mixed meat in the image of mixed meat was ±50% and ±75%. A sampling of mixed meat was not carried out on beef and pork that had been crushed. The image extension used in this study was *JPG.

Table 1.Image Data Used

No	Attribute	Number of Image
1	Beef Image	200
2	Pork Image	200
3	Mixed Meat Image	200
	Total	600

The dataset used in this study amounted to 600 images consisting of 200 beef images, 200 pork images, and 200 processed meat images as shown in Table 1. This study classified the adulterated image with the beef image or pork image.

2.2. Preprocessing

The initial stage of data preprocessing carried out in this research is cropping (Figure 3).

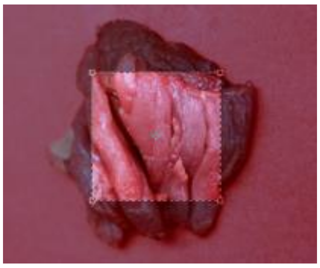

Figure 3. Cropping Process

Cropping is done to make it easier for the system to process image data and extract color and texture attributes. Cropping is done by hand with the photoshop CS6 program. This is accomplished by taking the needed image object and deleting the image background, resulting in a square cropping result.

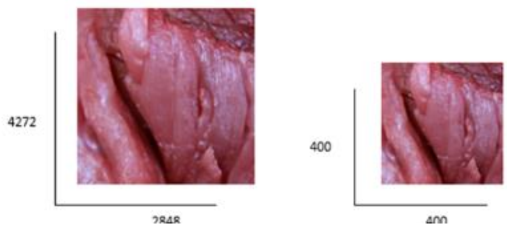

Figure 4. Resize Process

The next process is resizing (Figure 4). Resize is done to speed up the computing process. Resize is done by changing the pixel size of the image according to the desired size in the study. This study uses a size of 400×400 pixels.

2.3. Color Feature Extraction

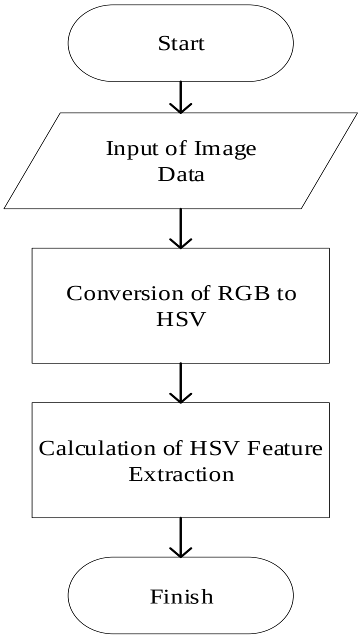

Figure 5. Stages of HSV Feature Extraction

HSV is a color feature extraction that defines in terms of Hue, Saturation, and Value. HSV feature extraction is connected to human vision and is the best color feature identification method among those currently available [13]. The image is blurred (not clear) in some circumstances, according to research conducted by [14]. Therefore this function can restore blurred photos that deal with brightness and saturation. The process of converting RGB values to HSV is carried out according to the equations (1), (2), and (3) [15].

$$H = tan\left[\frac{3(G-B)}{(G-B)+(R-B)}\right] \quad (4)$$

$$S = 1 - \frac{\min(R,G,B)}{V} \quad (5)$$

$$V = \frac{R+G+B}{3} \quad (6)$$

However, the above equation if the value of S=0 then H cannot be determined. Thus. it is necessary to normalize the RGB first based on the equations (7), (8), (9).

$$r = \frac{R}{R+G+B} \quad (10)$$

$$g = \frac{G}{R+G+B} \quad (11)$$

$$b = \frac{B}{R+G+B} \quad (12)$$

Where R,G,B is Unnormalized Red, Green and Blue values, and r,g,b is Normalized values of red, green and blue. After the RGB normalization process is carried

DOI: https://doi.org/10.29207/resti.v6i3.4067

out, then the RGB to HSV conversion process is carried out using the equation (13), (14), (15), (16).

$$v = \max\ (r, g, b) \tag{17}$$

$$s = \begin{cases} 0 \\ v \end{cases} \tag{18}$$

$$H = \begin{cases} 0 & If\ s = 0 \\ 60\ \times (-g - b) & if\ v = r \\ 60\ \times \left[2 + \frac{b-r}{s \times v}\right] & if\ v = g \\ 60\ \times \left[4 + \frac{r-g}{s \times v}\right] & if\ v = b \end{cases} \tag{19}$$

$$H\ = H + 360 \qquad If\ H < 0 \tag{20}$$

Where V is maximum value from r, g, and b. S is saturation value and H is Hue Value.

2.4. Texture Feature Extraction

Texture feature extraction is used to create a dominant local binary picture pattern for statistical characteristic extraction [16]. The most well-known feature extraction approach is GLCM, which is commonly utilized in the estimation of second-order statistical methods [17]. The first step in the GLCM approach is to convert an RGB Image to grayscale to obtain a gray image.

Conversion is done to simplify the process of image objects because grayscale pixels are only represented by one level of gray. Then, the process of making a co-occurrence matrix consisting 4 directions $\theta^{\circ}(0^{\circ}, 45^{\circ}, 90^{\circ}, 135^{0})$ and distance (d) to express how far the distance between two pixels, the matrix size used is 256×256. After obtaining the co-occurrence matrix, then the process of calculating the second-order statistical GLCM features, including contrast, correlation, homogenity, energy, dissimilarity, and Angular second moment (ASM).

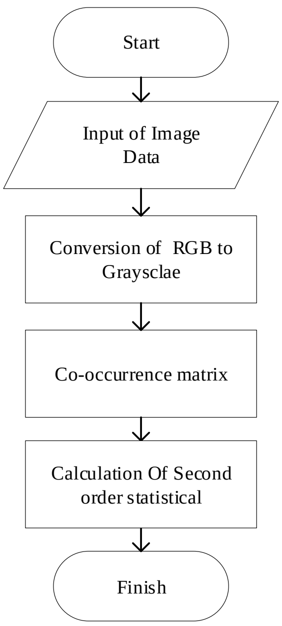

Figure 6. GLCM Feature Extraction

The process of calculating the second-order statistical value was performed by using equations (21), (22), (23), (24), (25), and (26) [18].

1. Contrast is used to calculate the gray range in the image. The bigger the difference, the higher the contrast and vice versa.

$$= \sum_i \sum_j |i - j|^2 p(i, j) \tag{27}$$

2. Correlation is used to calculate the linear dependence of the image with its neighbors. If the degree of gray between pixels has a linear relationship, the correlation will be high.

$$= \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \tag{28}$$

3. Homogenity is used to calculate the level of gray in the image, if the degree of gray is almost the same then the value of homogeneity is higher.

$$= \sum_{\mathrm{i}} \sum_{\mathrm{j}} \frac{1}{1+|\mathrm{i}-\mathrm{j}|^2} \mathrm{p}(\mathrm{i}, \mathrm{j}) \tag{29}$$

4. Energy describes the orderly level of distribution of gray levels in the image. The more regular, the higher the energy value.

$$= \sum_{i,j} p(i, j)^2 \tag{30}$$

5. Dissimilarity measures the difference in the average gray level of the image. The greater the value, the greater the difference in intensity values between neighboring pixels.

$$= \sum_i \sum_j |i - j| p(i, j) \tag{31}$$

6. Angular Second Moment (ASM) is used to show a measure of the homogeneity of an image [19].

$$= \sum_i \sum_j \{p(i, j)\}^2 \tag{32}$$

2.5. Fuzzy Learning Vector Quantization

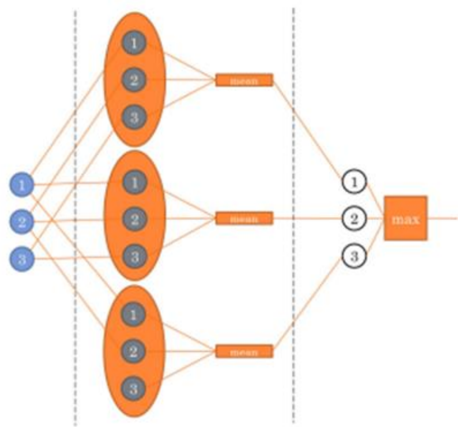

Figure 7. FLVQ Architecture [22]

The FLVQ algorithm was first introduced by Tsao (1994) [20] who combined the concepts of fuzzy and neural networks. Fuzzy theory is used to improve

DOI: https://doi.org/10.29207/resti.v6i3.4067

performance and deal with the weaknesses of the LVQ algorithm [21]. This theory is needed to determine the winning class because the LVQ algorithm determines the winning class based on the results of the competition on each neuron [22] using Euclidean distance to determine the input vector[23].

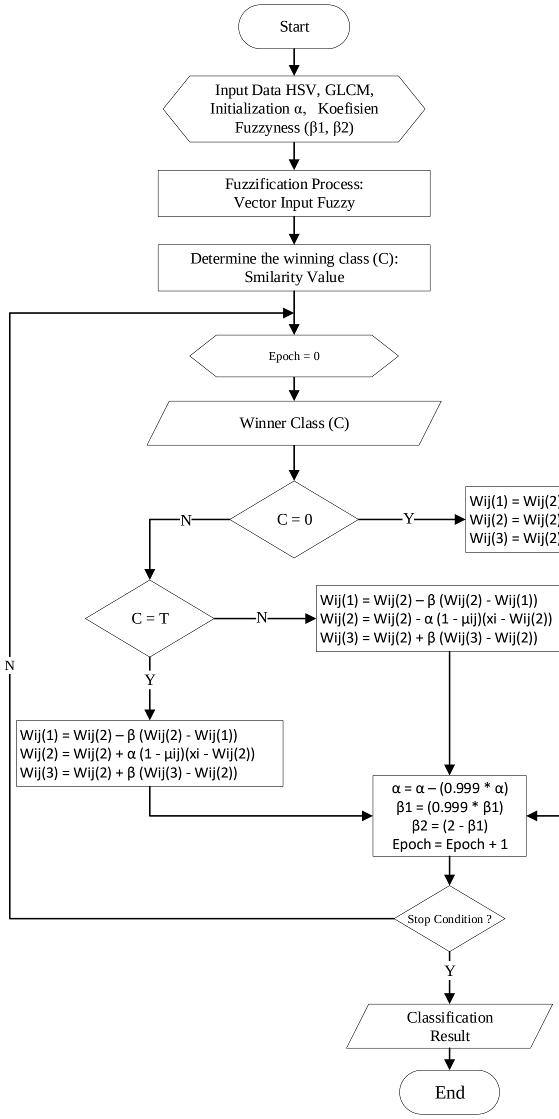

Figure 8 Flowchart Fuzzy Learning Vector Quantization

The FLVQ architecture (Figure 7) is almost the same as the LVQ architecture, but FLVQ has a hidden layer (cluster). The neurons in the input layer are connected to the hidden layer (cluster-of-neurons) which are grouped by meat category so that the number of cluster-of-neurons is as much as the meat category in the input vector. The process of the FLVQ algorithm can be seen in Figure 8.

$$\tilde{x} = \left(x^{(1)}, x^{(2)}, x^{(3)}\right) \quad (33)$$

where $x^{(1)}$ is the minimum value, $x^{(2)}$ is the value of the midpoint of the peak, and $x^{(3)}$ is the maximum value [24]. To deal with the fuzziness caused by errors in statistical measurements, FLVQ uses fuzzy numbers to determine the activity of these neurons (Figure 9).

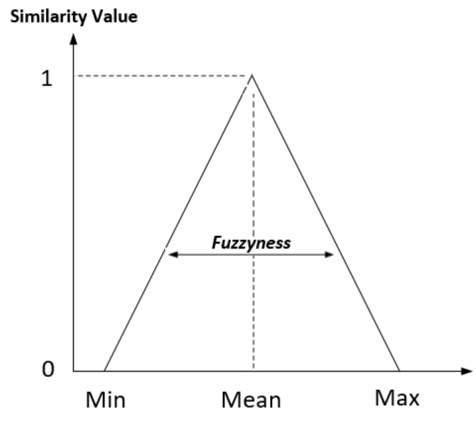

Figure 9. Fuzzy Triangle Representation

DOI: https://doi.org/10.29207/resti.v6i3.4067

The process of fuzzification of all reference components and input vectors is expressed in triangular fuzzy numbers [25] as Equation (33).

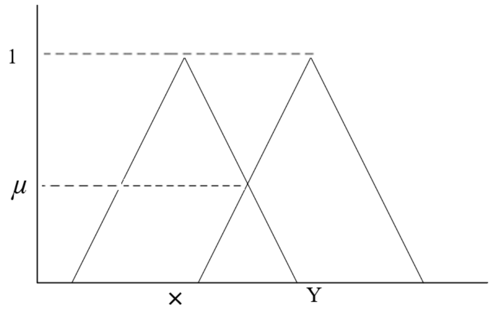

Figure 10. Similarity Value

$$\mu(\times,\gamma) = \frac{\gamma - \times^{(3)}}{\times^{(2)} - \times^{(3)}} \quad (34)$$

Because the data representation is converted into fuzzy numbers, then the distance measurement on the LVQ is also replaced by similarity value calculation was performed based on Figure 10, which was by calculating the intersection between the two triangles [22]. The similarity value can be calculated using equation $\mu\times,\gamma = \frac{\gamma - \times^{(3)}}{\times^{(2)} - \times^{(3)}}$ (34). The FLVQ algorithm has 3 conditions in the weight update [24]. First, there is no winning codebook because all the maximum similarity values are 0 so the data is considered not to fall into any class (equations $Wij(1) = W_{ij}^{(2)} - \beta\left(W_{ij}^{(2)} - W_{ij}^{(1)}\right)$ (35), $Wij(2) = W_{ij}^{(2)}$ (36), $Wij(3) = W_{ij}^{(2)} + \beta(W_{ij}^{(3)} - W_{ij}^{(2)})$ (37)).

$$W_{ij}^{(1)} = W_{ij}^{(2)} - \beta\left(W_{ij}^{(2)} - W_{ij}^{(1)}\right) \quad (35)$$

$$W_{ij}^{(2)} = W_{ij}^{(2)} \quad (36)$$

$$W_{ij}^{(3)} = W_{ij}^{(2)} + \beta(W_{ij}^{(3)} - W_{ij}^{(2)}) \quad (37)$$

With the value of the fuzziness coefficient (β >1). Second, the codebook with the maximum similarity value belongs to the same class as the input vector so that the codebook is closer to the input vector and produces higher similarity. Calculations are made based on equation ($Wij(2) = W_{ij}^{(2)} + \alpha(1 - \mu_{ij})(\times_i - W_{ij}^{(2)})$ (38).

$$W_{ij}^{(2)} = W_{ij}^{(2)} + \alpha(1 - \mu_{ij})(\times_i - W_{ij}^{(2)}) \quad (38)$$

With the condition of the fuzziness coefficient (β >1), the value of α is the learning rate. Third, the codebook with the maximum similarity value is not included in the same class as the input vector so that the triangular function moves away from the input vector according to equation (39) where the fuzziness coefficient (β < 1).

$$W_{ij}^{(2)} = W_{ij}^{(2)} - \alpha(1 - \mu_{ij})(\times_i - W_{ij}^{(2)}) \quad (39).$$

3. Result and Discussion

Experimental parameters were carried out with several test schemes as shown in Table 2.

Table 2. Test Parameters

No	Experimental Testing	Parameter Configuration
1	Learning Rate (α)	The decrease of time function which can influence speed. If LR is too small then algorithm will take long time to converge and if LR is too big then algorithm becomes divergent. LR used were 0,01; 0,02; 0,03; 0,04; 0,05
2	Fuzzyness Coefficient (β)	Coefficient used in the process of weight changing in FLVQ Classification. FLVQ Fuzziness Coefficient is divided into 2 namely widening coefficient and narrowing coefficient.
	• Widening (β1)	1,01; 1,02; 1,03; 1,04; 1,05
	• Narrowing (β2)	0,2; 0,3; 0,4; 0,5; 0,6

Table 3 depicts the experimental environment used to determine the viability of the suggested approach. The test is run to see how the test results are affected by the parameters utilized.

Table 3. Experimental Environment

No	Simulation environment	Environment Configuration
1	Software	Phyton
2	Operation System	Windows10
3	CPU	AMD Ryzen 7 5700U
4	Memory	8 GB

The proposed strategy's performance will be compared to research [3] to evaluate which has the greatest outcomes in terms of data recognition accuracy, including training and testing data.

Table 4. Identification Results of Beef and Pork Class

Widening (β1)	Narrowing (β2)	Learning Rate	Accuracy
		0,01	90,00%
		0,02	85,00%
	0,2	0,03	85,00%
		0,04	90,00%
		0,05	100,00%
		0,01	82,50%
		0,02	90,00%
	0,3	0,03	82,50%
		0,04	90,00%
		0,05	70,00%
		0,01	82,50%
		0,02	87,50%
1,01	0,4	0,03	82,50%
		0,04	87,50%
		0,05	62,50%
		0,01	95,00%
		0,02	75,00%
	0,5	0,03	77,50%
		0,04	70,00%
		0,05	65,00%
		0,01	67,50%
		0,02	65,00%
	0,6	0,03	80,00%
		0,04	75,00%
		0,05	80,00%

DOI: https://doi.org/10.29207/resti.v6i3.4067

Thus, after the testing procedure is completed, it can be determined whether the algorithm can recognize the image of beef, pig, or mixed meat. Image data of beef, pork, and mixed meat is used in the research, which is based on a mixture of color feature extraction and meat texture feature extraction. Data sharing is done using K-fold validation, with several folds of 10.

The first test scenario uses beef and pork image data without using adulterated images, this is done to see the results of the model recognition level applied to the image.

Table 5. Results of Classification of Beef and Mixed Meat

Widening (β1)	Narrowing (β2)	Learning Rate	Accuracy
		0,01	77,50%
		0,02	92,50%
	0,2	0,03	87,50%
		0,04	90,00%
		0,05	90,00%
		0,01	80,00%
		0,02	90,00%
	0,3	0,03	80,00%
		0,04	85,00%
		0,05	80,00%
		0,01	85,00%
		0,02	92,50%
1,03	0,4	0,03	95,00%
		0,04	90,00%
		0,05	85,00%
		0,01	87,50%
		0,02	70,00%
	0,5	0,03	77,50%
		0,04	90,00%
		0,05	75,00%
		0,01	70,00%
		0,02	67,50%
	0,6	0,03	80,00%
		0,04	75,00%
		0,05	95,00%

The distribution of training data and testing data in this first scenario is performed based on K-fold validation with a fold value of 10. The training data used is 360 and the testing data is 40 data consisting of pork images and beef images.

The test scenarios were carried out on beef and pork classes using the widening fuzziness coefficient parameter (β1) 1,01; 1,02; 1,03; 1,04; 1,05, narrowing *fuzzyness* coefficient (β2) 0,2; 0,3; 0,4; 0,5; 0,6, and the learning rates used are 0,01; 0,02; 0,03; 0,04; 0,05. The best accuracy results obtained in the first test scenario are seen in Table 4 with the highest percentage of accuracy results being 95.00% at a learning rate of 0.05 with an epoch of 100. The coefficient of widening fuzziness (β1) is 1,01 and the coefficient of narrowing (β2) is 0,2.

The second test scenario was performed by using the image data of beef and mixed meat without using the image of pork. This is done to see the level of image recognition of beef and mixed meat from the applied model. This second scenario uses the same parameters as the first scenario. The distribution of data in the second scenario is done by K-fold validation using a fold value of 10. The amount of training data used is 360 and the testing data used is 40. The best accuracy results from the second scenario are seen in Table 5 with the highest percentage of accuracy results being 95.00% with a learning rate of 0.03 and 0.05, a widening fuzziness coefficient of 1.03, and a narrowing coefficient of 0.4 and 0.6.

Table 6. Identification Results of Pork and Mixed Meat Class

Widening (β1)	Narrowing (β2)	Learning Rate	Accuracy
		0,01	92,50%
		0,02	85,00%
	0,2	0,03	82,50%
		0,04	95,00%
		0,05	80,00%
		0,01	90,00%
		0,02	90,00%
	0,3	0,03	87,50%
		0,04	72,50%
		0,05	87,50%
		0,01	70,00%
		0,02	85,00%
1,02	0,4	0,03	80,00%
		0,04	87,50%
		0,05	77,50%
		0,01	67,50%
		0,02	67,50%
	0,5	0,03	67,50%
		0,04	70,00%
		0,05	72,50%
		0,01	70,00%
		0,02	70,00%
	0,6	0,03	75,00%
		0,04	72,50%
		0,05	70,00%

The third test scenario employs pork and mixed meat image data instead of beef image data. Table 6 shows the greatest results from evaluating the third scenario, with a 95.00 percent accuracy rate at a learning rate of 0.04, a widening coefficient of 1.02, and a narrowing coefficient of 0.2. This scenario uses the same training and testing data as the previous test scenario, which used K-fold validation with a total of 10 folds.

Table 7. Identification Results of Pork and Beef Class

No.	Learning Rate	Proposed Strategy	Research [3]
1.	0,01	87,50%	67,50%
2.	0,02	90,00%	67,50%
3.	0,03	95,00%	67,50%
4.	0,04	97,50%	67,50%
5.	0,05	100,00%	67,50%

The fourth test scenario compares the accuracy results obtained by the proposed strategy with research [3]. The data used in this fourth scenario is the image of beef and the image of pork without using the image of mixed meat. This fourth test scenario was carried out to see the results of the accuracy performance of the proposed strategy and research [3]] in recognizing the image of beef and pork image.

The results of the accuracy performance of the fourth scenario can be seen in Table 7. The proposed outperformed the previous studies [3]. With a learning

DOI: https://doi.org/10.29207/resti.v6i3.4067

rate of 0.05 and a widening fuzziness coefficient ((β1) 1,01 narrowing coefficient (β2) 0,2, the proposed method achieves the best percentage accuracy in the fourth scenario.

Table 8. Identification Results of Beef Class and Mixed Meat

No.	Learning Rate	Proposed Strategy	Research [3]
1.	0,01	92,50%	82,50%
2.	0,02	92,50%	82,50%
3.	0,03	95,00%	82,50%
4.	0,04	95,00%	82,50%
5.	0,05	97,50%	82,50%

Without employing pork data, the fifth test scenario employs beef and mixed meat data. The fifth test scenario is the same as the fourth, in that it examines performance based on the proposed and research strategy's correctness [3]. Table 8 displays the results of the fifth scenario's identification. The proposed strategy got better results than the research [3]. The highest percentage of accuracy performance in the fifth scenario is 97.50% with a learning rate of 0.05, widening coefficient (β1) 1,04, and narrowing coefficient (β2) 0,4.

Table 9. Classification Results of Pork and Mixed Meat

No.	Learning Rate	Proposed Strategy	Research [3]
1.	0,01	92,50%	85,00%
2.	0,02	95,00%	85,00%
3.	0,03	90,00%	85,00%
4.	0,04	95,00%	85,00%
5.	0,05	90,00%	85,00%

The sixth test scenario is the same as the fourth and fifth test situations where it compares the correctness of the proposed and research strategies [3]. Without employing beef, the sixth test uses pork and mixed meat classes. Without employing pork data, the fifth test scenario employs beef and mixed meat data. The fifth test scenario is the same as the fourth, in that it examines performance based on the proposed and research strategy's correctness [3]. Table 8 displays the results of the fifth scenario's identification. The proposed strategy got better results than the research [3]. The highest percentage of accuracy performance in the fifth scenario is 97.50% with a learning rate of 0.05, widening coefficient (β1) 1,04, and narrowing coefficient (β2) 0,4.

Table 9 shows the results of the sixth test scenario. Based on the highest percentage of accuracy, 95.00 percent, at learning rates of 0.02 and 0.04, widening fuzziness coefficients of 1.04 and 1.05 with narrowing fuzziness coefficients of 0,4 and 0.2, the proposed is superior. For each learning rate, the six research test scenarios [3] yield the same proportion of accuracy outcomes, which is 85.00%.

4. Conclusion

The study makes use of numerous forms of image data, including images of pork, beef, and mixed meat. The study were divided into three categories: beef and pork classes, beef and mixed meat classes, and pork and mixed meat classes. The data used in each image is 200 data so the total data used is 400 data in each test scenario category.

The proposed strategy achieves better results in each test scenario, with the pork and beef classes having the highest percentage accuracy of 100.00%. The proposed strategy achieves the highest accuracy of 97.50 % in the beef and mixed meat category, and 95.00 % in the pork and mixed meat category. The accuracy results for the research [3] were 67.50 % in the pork and beef class, 82.50 % in the beef and mixed meat class, and 85.00 % in the pork and mixed meat class. This result demonstrates that the proposed strategy can separate pork from beef, beef from mixed meat, and pork from mixed meat. The use of HSV color feature extraction and GLCM texture feature extraction provides good features that allow the FLVQ algorithm to classify pork, beef, and mixed meat.

References

[1] L. Arsilo and K. Ma'mur, "Implementasi Sistem Klasifikasi Analisa Tekstur Dan Normalisasi Warna Terhadap Daging Sapi Dan Daging Babi," vol. 1, no. 03, pp. 216–224, 2022.

[2] N. A. Nafiasari and A. M. Handayani, "Penganalisis kesegaran daging sapi dan daging babi mentah berdasarkan klasifikasi warna dan kelembaban," vol. 6131, pp. 66–74, 2018, doi: 10.22146/teknosains.35643.

[3] U. Sudibyo, D. P. Kusumaningrum, E. H. Rachmawanto, and C. A. Sari, "Optimasi Algoritma Learning Vector Quantization (Lvq) Dalam Pengklasifikasian Citra Daging Sapi Dan Daging Babi Berbasis GLCM Dan HSV," *Simetris J. Tek. Mesin, Elektro dan Ilmu Komput.*, vol. 9, no. 1, pp. 1–10, 2018, doi: 10.24176/simet.v9i1.1943.

[4] R. A. Asmara *et al.*, "Classification of pork and beef meat images using extraction of color and texture feature by Grey Level Co-Occurrence Matrix method," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 434, no. 1, p. 012072, Nov. 2018, doi: 10.1088/1757-899X/434/1/012072.

[5] Jasril and S. Sanjaya, "Learning Vector Quantization 3 (LVQ3) and Spatial Fuzzy C- Means (SFCM) for Beef and Pork Image Classification," vol. 1, no. 2, pp. 60–65, 2018.

[6] L. Handayani, "Analisa Metode Gabor dan Propbabilistic Neural Network untuk Klasifikasi Citra (Studi Kasus : Citra Daging Sapi dan Babi)," vol. 14, no. 2, pp. 169–177, 2017.

[7] D. R. Wijaya, R. Sarno, and A. F. Daiva, "Electronic nose for classifying beef and pork using Naïve Bayes," *Proc. - 2017 Int. Semin. Sensor, Instrumentation, Meas. Metrol. Innov. Adv. Compet. Nation, ISSIMM 2017*, vol. 2017-January, pp. 104–108, Nov. 2017, doi: 10.1109/ISSIMM.2017.8124272.

[8] L. Bing and W. Wang, "Sparse Representation Based Multi-Instance Learning for Breast Ultrasound Image Classification," *Comput. Math. Methods Med.*, vol. 2017, 2017, doi: 10.1155/2017/7894705.

[9] D. Wandi, Fauziah, and N. Hayati, "Deteksi kelayuan bunga mawar dengan metode transformasi ruang warna hsi dan hsv," vol. 5, no. 3, pp. 333–341, 2021.

[10] Ş. Öztürk and B. Akdemir, "Application of Feature Extraction and Classification Methods for Histopathological Image using GLCM , LBP, LBGLCM, GLRLM, and SFTA," *Procedia Comput. Sci.*, vol. 132, no. Iccids, pp. 40–46, 2018, doi: 10.1016/j.procs.2018.05.057.

[11] H. Himawan and W. Wiratama, "Different Types of Beef And Pork Using Histogram Texture Anda K-Means Clustering Method," vol. 3, no. 1, pp. 20–27, 2018.

[12] F. Zhang *et al.*, "Application of Quantum Genetic Optimization

DOI: https://doi.org/10.29207/resti.v6i3.4067

of LVQ Neural Network in Smart City Traffic Network Prediction," *IEEE Access*, vol. 8, pp. 104555–104564, 2020, doi: 10.1109/ACCESS.2020.2999608.

[13] J. M. Chaves-González, M. A. Vega-Rodríguez, J. A. Gómez-Pulido, and J. M. Sánchez-Pérez, "Detecting skin in face recognition systems: A colour spaces study," *Digit. Signal Process.*, vol. 20, no. 3, pp. 806–823, May 2010, doi: 10.1016/J.DSP.2009.10.008.

[14] Y. Wan and Q. Chen, "Joint image dehazing and contrast enhancement using the HSV color space," *2015 Vis. Commun. Image Process. VCIP 2015*, vol. 1, no. 3, pp. 2–5, 2015, doi: 10.1109/VCIP.2015.7457892.

[15] E. Budianita, Jasril, and L. Handayani, "Implementasi Pengolahan Citra dan Klasifikasi K-Nearest Neighbour Untuk Membangun Aplikasi Pembeda Daging Sapi dan Babi Berbasis Web," *J. Sains dan Teknol. Ind.*, vol. 12, no. Vol 12, No 2 (2015): Juni 2015, pp. 242–247, 2015, [Online]. Available: http://ejournal.uin-suska.ac.id/index.php/sitekin/article/view/1005.

[16] M. Garg and G. Dhiman, "A novel content-based image retrieval approach for classification using GLCM features and texture fused LBP variants," *Neural Comput. Appl. 2020 334*, vol. 33, no. 4, pp. 1311–1328, Jun. 2020, doi: 10.1007/S00521-020-05017-Z.

[17] A. Ali, X. Jing, and N. Saleem, "GLCM-based fingerprint recognition algorithm," in *Proceedings - 2011 4th IEEE International Conference on Broadband Network and Multimedia Technology, IC-BNMT 2011*, 2011, pp. 207–211, doi: 10.1109/ICBNMT.2011.6155926.

[18] P. K. Mall, P. K. Singh, and D. Yadav, "GLCM based feature extraction and medical X-RAY image classification using machine learning techniques," *2019 IEEE Conf. Inf. Commun. Technol. CICT 2019*, pp. 1–6, 2019, doi: 10.1109/CICT48419.2019.9066263.

[19] S. A. Wibowo, B. Hidayat, and U. Sunarya, "Simulasi dan Analisis Pengenalan Citra Daging Sapi dan Daging Babi dengan Metode GLCM," pp. 338–343, 2016.

[20] A. Damayanti, "Fuzzy learning vector quantization, neural network and fuzzy systems for classification fundus eye images with wavelet transformation," *Proc. - 2017 2nd Int. Conf. Inf. Technol. Inf. Syst. Electr. Eng. ICITISEE 2017*, vol. 2018-January, pp. 331–336, Feb. 2018, doi: 10.1109/ICITISEE.2017.8285522.

[21] P. Utomo, Wiharto, and E. Suryani, "Sistem Diagnosa Penyakit Paru Berdasarkan Foto Rontgen Dengan Pendekatan Fuzzy Learning Vector Quantization," *ITSMART J. Teknol. dan Inf.*, vol. 1, no. 2, pp. 102–106, Mar. 2016, doi: 10.20961/ITSMART.V1I2.604.

[22] W. Jatmiko *et al.*, "Development of Adaptive Fuzzy-Neuro Generalized Learning-Vector Quantization Using PI Membership Function (AFNGLVQ-PI)," *IEEEAccess*, 2021. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9343316 (accessed Jul. 14, 2021).

[23] M. Rabin and M. Rahwi, "Klasifikasi Kualitas Susu Segar Menggunakan Metode Fuzzy Learning Vector Quantization," 2018.

[24] F. Syafria, A. Buono, and P. Silalahi, "Pengenalan Suara Paru-Paru dengan MFCC sebagai Ekstraksi Ciri dan Backpropagation sebagai Classifier Lung Sound Recognition using MFCC as A Feature Extraction and Backpropagation as A Classifier," 2014, Accessed: Jun. 28, 2021. [Online]. Available: http://journal.ipb.ac.id/index.php/jika.

[25] W. Jatmiko, Rochmatullah, B. Kusumoputro, K. Sekiyama, and T. Fukuda, "Fuzzy learning vector quantization based on particle swarm optimization for artificial odor dicrimination system," *WSEAS Trans. Syst.*, vol. 8, no. 12, pp. 1239–1252, 2009.

[26] M. F. Rachmadi, M. A. Ma'sum, I. M. A. Setiawan, and W. Jatmiko, "Fuzzy Learning Vector Quantization Particle Swarm Optimization (FLVQ-PSO) and Fuzzy Neuro Generalized Learning Vector Quantization (FN-GLVQ) for Automatic Early Detection System of Heart Diseases based on Real-time Electrocardiogram," pp. 465–470, 2012.

DOI: https://doi.org/10.29207/resti.v6i3.4067