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Evaluation of Wavelet and Gray Level Co-Occurrence Matrix Combination Model for Texture Image Feature Extraction of Various Types of Meat

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ABSTRACT

The purpose of this research is to evaluate the combination of Wavelet and Gray Level Co-occurrence Matrix (GLCM) methods in extracting texture features of various types of meat, including beef, buffalo, lamb, horse, and pork. This method integrates the advantages of wavelet transform in capturing spatial-frequency features with GLCM's ability to analyse statistical texture patterns. The classification process is carried out using the k-Nearest Neighbors (k-NN) algorithm, and the model accuracy is evaluated using a confusion matrix. The research results show that the combination of Wavelet and GLCM features significantly improves the classification performance, with an average accuracy of 97.2%. Further analysis shows that the integration of these two methods provides better classification results between fresh, frozen, and rotten categories for each type of meat. Although there are some classification errors, the overall results show the reliability and effectiveness of this approach. Further research can explore parameter optimization or the integration of more sophisticated classification algorithms.

1. INTRODUCTION

The meat industry is an important sector in meeting food needs worldwide. Meat quality is greatly influenced by various factors, such as the type of animal, the age of the animal, the slaughtering process, and the processing and storage methods [1]. One aspect of quality that is very important and can affect consumer acceptance is meat texture. Meat texture, which includes tenderness, roughness, elasticity, and density, greatly affects consumer acceptance of the product [2]. In addition, the physical condition of the meat, whether fresh, frozen, or rotten, also plays a major role in determining the quality of the texture that can be observed in the meat image [3]. Changes in this physical condition will change the texture properties of the meat, which can be observed through digital image processing techniques [4].

Fresh meat tends to have a chewy, soft, and elastic texture, with a smooth surface and little or no wrinkles. In contrast, frozen meat has a harder, stiffer, and more porous texture due to freezing, which causes changes in muscle fibres and the structure of meat tissue. Rotten meat, on the other hand, has a softer, more watery, and disintegrating texture due to the decomposition processes that damages muscle fibres and tissue. Therefore, the analysis of meat texture is not only limited to the type of meat, but also needs to consider changes in texture that occur due to differences in physical conditions, such as fresh, frozen, or rotten.

Traditionally, meat texture quality assessment is carried out through physical methods involving laboratory testing or sensory tests conducted by experts. However, these methods require a lot of time, money, and effort. With the advancement of technology, digital image analysis has emerged as a more efficient and accurate solution for automatically assessing meat texture [5].

Research related to meat image classification has been conducted in recent years by several researchers. The ResNet152V2 algorithm was employed to classify beef, lamb and pork types, achieving 80% accuracy on a dataset of 585 images [6].

Beef quality can be checked visually by observing the colour or texture of beef using the human eye. Beef quality can be evaluated visually by examining the colour or texture of the meat using direct observation by the human eye. Although this manual method is relatively simple, it is very subjective due to differences in understanding the characteristics of fresh or damaged beef, as well as variations in the level of accuracy. The use of a combination of colour and texture features for meat image classification was carried out using Support Vector Machines, statistical approaches and the GLCM method for the feature extraction process with a total data used of 480 images, obtaining the highest accuracy of 97% [7]. Furthermore, A combination of HSV (hue, saturation, value) color features and LOOP (Local Optimal-Oriented Pattern) texture features was employed, achieving 98%-100% accuracy on a dataset of 400 images [8].

These researches have produced a high level of accuracy in identifying the quality of certain meats, namely beef and pork. However, these researches have not used variations in image data for other types of meat, namely buffalo, lamb, and horse meat. The quality studied is still limited to fresh and damaged (rotten) meat.

For this reason, this research proposes an evaluation of the combination model of Wavelet and GLCM for the extraction of texture image features of various types of meat (beef, lamb, buffalo, horse, pork) based on quality, namely fresh, frozen and rotten.

This research contributes to improving the accuracy of meat image texture classification based on its quality. By using a combination of Wavelet and GLCM, this research can provide more precise results in identifying meat quality, whether it is fresh, frozen, or rotten. This is important for monitoring the quality of meat products, which in turn can be applied in automation systems for inspection and quality control in the food industry, thereby helping manufacturers ensure more consistent product quality.

In addition, the combination of these two methods is expected to produce a more accurate and robust texture classification system. Wavelet transform will capture texture patterns globally and multi-scale, while GLCM applied to the results of wavelet decomposition will extract more specific local spatial relationships.

2. RELATED WORK

Wavelet transform has been used in several research for texture feature extraction from images. Wavelet allows image decomposition into various frequencies and scales, which is useful in identifying more complex texture patterns in images [9]. Wavelet transform has been applied to identify young green tea leaves in color images [10]. For improved material and texture classification in object identification, wavelet transform has been combined with Convolutional Neural Networks (CNNs) [11]. In document image classification, a novel approach integrating wavelet transform with Swin Transformer has been proposed [12].

The measurement parameters of beef tenderness cannot be used for visual assessment, because they do not have visual standards. In the study [13], a method was developed to extract beef texture as a basic feature in the beef classification process using statistical analysis of GLCM and frequency domain of Discrete Wavelet Transform (DWT). The findings of this research indicate that beef texture, measured using a feature extraction method based on GLCM and DWT, can be used to assess beef tenderness effectively.

The future work in this research focuses on evaluating various texture features produced by both methods, including contrast, correlation, energy, and homogeneity from GLCM, as well as horizontal, vertical, and diagonal details from wavelet. Unlike previous research that was limited to only one type of meat or type of extraction method, this research expands the scope by testing the combination of Wavelet and GLCM techniques for various types of meat and assessing the model's ability to provide more accurate and efficient results in meat quality classification.

Empirical evidence from previous studies shows that the use of texture features from GLCM individually is indeed able to provide strong local statistical information. However, when GLCM is combined with multi-resolution information from wavelet transform, the classification performance can be significantly improved. In addition, wavelet transform has advantages in analyzing non-stationary signals and complex texture structures because of its ability to extract information at various scales and frequencies simultaneously [14]. This makes wavelet very suitable for image processing applications that require the detection of fine patterns and texture changes, such as in meat images. By combining the power of GLCM spatial analysis and the multi-resolution capabilities of wavelet, this approach is believed to be able to produce a more adaptive and accurate texture classification system for various types of meat.

3. METHODOLOGY

This research was conducted systematically for the classification of meat image textures based on their quality by utilizing digital image processing technology. Meat images were collected and grouped into three types of meat (beef, lamb, buffalo, horse, pork) with the quality categories studied, namely fresh, frozen and rotten.

Figure 1 shows a block diagram of the research stages that will be carried out.

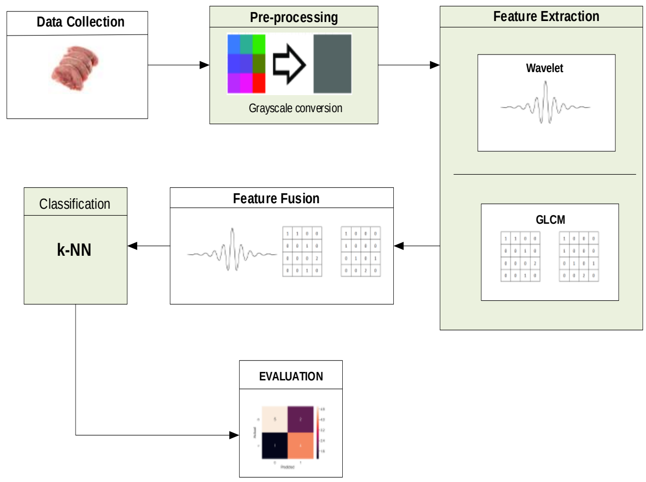

Figure 1. Research stages

3.1 Data collection

The meat type dataset in this research was taken using a digital camera, photographed with the same light intensity and distance. There are 5 types of meat, namely beef, buffalo, lamb, horse and pork. Each type of meat was taken as many as 50 meat images and then photographed one by one, so that the total data used was 750 images.

Table 1 shows sample images of various types of meat with fresh, frozen, and rotten qualities.

Based on Table 1, it can be observed that each image composition of meat types (beef, buffalo, lamb, horse, and pork) has the same number of samples for each category (fresh, frozen, and rotten). Each category has 50 samples per type of meat, so the total samples per type of meat is 150 samples. So the total samples of all types of meat are: 150 samples/meat ×5 categories of meat types =750 samples.

Table 1. Image samples of different types of meat (fresh, frozen, and rotten)

Meat Types	Category	Image	Number of Samples
Beef	Fresh		50
	Frozen		50
	Rotten		50
Buffalo	Fresh		50
	Frozen		50
	Rotten		50
Lamb	Fresh		50
	Frozen		50
	Rotten		50
Horse	Fresh		50
	Frozen		50
	Rotten		50
Fork	Fresh		50
	Frozen		50
	Rotten		50
	Total Samples:		**750**

3.2 Pre-processing

The first stage carried out in image pre-processing is cropping. This process is the cutting of pixels in a digital image according to the specified position and dimensions [14]. This cutting process is carried out based on spatial coordinates in vector format [x, y, width, height], which includes all pixels within the specified area. Furthermore, resizing is carried out to change the image size from 6000 × 4000 pixels to 100 × 500 pixels. This step aims to reduce computing time and the load on the system. The last stage is the conversion of the colour image to grayscale. This process is important for feature extraction using the GLCM to ensure more accurate texture analysis. Sample images produced from pre-processing can be seen in Figure 2.

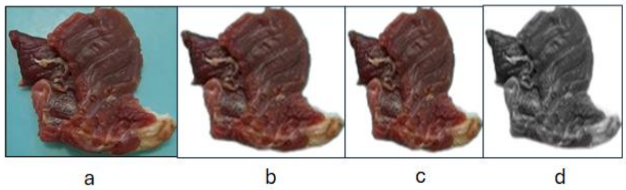

Figure 2. Pre-processing: (a). Original beef image sample, (b). Cropped image, (c). Resized image 100 × 500, (d). Convert color image to grayscale image

3.3 Feature extraction

Feature extraction is the process of extracting features from an image that are needed for classification purposes [15]. In this research, feature extraction was carried out using two main methods, namely wavelet transformation (including Haar wavelet, Daubechies, Coiflets, Symlet) and GLCM.

In wavelet transform, the image is decomposed into several coefficients that describe the intensity changes at various scales and orientations. These coefficients include LL (Low-Low), LH (Low-High), HL (High-Low), and HH (High-High). The LL coefficients store the average or approximation information of the image at low scales, describing the basic structure of the image. Meanwhile, the LH, HL, and HH coefficients store the image details in the horizontal, vertical, and diagonal directions with different resolutions, each describing the texture changes in the image. By using various types of wavelets such as Haar, Daubechies, Coiflet, and Symlet, these coefficients can provide different descriptions of the image texture, depending on the wavelet's ability to capture details at various frequency levels [16, 17].

Furthermore, GLCM functions to calculate the frequency of occurrence of pixels with a certain gray intensity that are adjacent to other pixels in various directions, including horizontally, vertically, and diagonally right and left [18]. The feature extraction process produces statistical parameters, namely contrast, correlation, energy, homogeneity and entropy [19, 20]. Energy can be calculated using Eq. (1).

$$Energy = \sum_{i}\sum_{j} P\,(i,j)^2 \tag{1}$$

Contrast, also known as inertia, is a measure that describes the degree of variation in the intensity of different pixels in an image. Contrast can be calculated by Eq. (2).

$$Contrast = \sum_i \sum_j (i-j)^2 * P(i,j) \quad (2)$$

Homogeneity is a measure that reflects the level of matrix elements that are close to the diagonal of the GLCM matrix. The homogeneity value will be high if the matrix elements that have high values are located near the diagonal. Homogeneity can be calculated using Eq. (3).

$$Homogeneity = \sum_i \sum_j \frac{P(i,j)}{1+(i-j)^2} \quad (3)$$

Entropy is a measure of the complexity of the texture or information contained in an image. Entropy can be calculated using Eq. (4).

$$Entropy = -\sum_i \sum_j P(i,j) * log\, P\,(i,j) \quad (4)$$

Correlation is a measure that describes the degree of relationship between two pixels. Correlation can be calculated using Eq. (5).

$$Corelation = \frac{\sum_i \sum_j * P(i,j) - \mu_{x*}\mu_y}{\sigma_x * \sigma_y} \quad (5)$$

3.4 Feature fusion

Feature Fusion is a technique in machine learning and computer vision that combines features from multiple sources or multiple levels of representation to improve model performance [21]. This process is often used in a variety of applications, such as image classification, object detection, and segmentation, where more and more diverse information can provide a better understanding of the data [22].

3.5 Classification with k-NN

Classification in machine learning is one of the tasks that aims to map input data into certain categories or classes based on patterns in the data [23]. One of the methods commonly used in classification is k-NN. k-NN is an instance-based learning algorithm used for classification and regression. In the case of classification, this algorithm groups data into certain classes based on their proximity to other data that has been labeled [24, 25].

3.6 Evaluation

Evaluation in machine learning is a very important step to assess the performance of a trained model and measure how well the model is able to solve the problem at hand [26]. Evaluation aims to find out whether the model can generalize well on data that has never been seen before and whether the model is robust enough to handle various conditions.

In the evaluation process, the data must first be divided into several subsets, namely training data to train the model, validation data to select the best model, and test data used to test the model's performance after training [27, 28]. Next, evaluation metrics are used to assess the model's results. In image classification, metrics such as accuracy, precision, recall, and F1-score are often used. Accuracy measures how often a model makes correct predictions, while precision and recall assess the model's ability to identify the correct class.

4. RESULTS AND DISCUSSION

This section presents the research results and analysis on the evaluation of the combination model of Wavelet and GLCM for the extraction of texture image features of various types of meat.

To conduct testing, a set of collected datasets was divided into 80% training data and 20% test data. This testing was conducted by comparing the results of feature extraction and meat classification using a single method (only wavelet or only GLCM) and a combination of both.

4.1 Wavelet

The test scenario is compiled based on various types of meat (beef, buffalo, lamb, horse, fork) which each have different condition categories (fresh, frozen, rotten), then tested using four different types of wavelets, namely Haar (H), Daubechies (D), Coiflets (C), and Symlet (S). This scenario aims to evaluate the performance of the model in extracting texture features of meat images in various conditions and types of meat using the wavelet transform technique. Table 2 shows the results of feature extraction using wavelet transform

Based on the results of feature extraction using wavelet transform presented in Table 2, it can be seen that the wavelet transform technique using four types of wavelets, namely Haar, Daubechies, Coiflets, and Symlet, has different performance in extracting texture features of meat images in various types and conditions. In general, Haar Wavelet gives the highest average results (87.42%), followed by Daubechies (85.81%), Coiflets (83.32%), and Symlet (83.26%). This indicates that Haar is superior in capturing texture information compared to other wavelets because Haar has a high ability to recognize small differences in image surface patterns, which are often important indicators in distinguishing meat conditions. Meanwhile, the performance of Coiflets and Symlets is almost the same, but still lower than Haar and Daubechies.

Table 2. Feature extraction results using wavelet transform

Type of Meat	Category	Wavelet			
		H	**D**	**C**	**S**
Beef	Fresh	89.21	87.12	85.46	85.65
	Frozen	88.76	86.89	84.12	83.26
	Rotten	96.82	85.44	82.76	82.21
Buffalo	Fresh	89.56	85.23	83.29	83.21
	Frozen	86.33	83.56	81.19	81.86
	Rotten	87.67	82.11	79.28	79.01
Lamb	Fresh	84.78	82.43	80.27	80.14
	Frozen	82.11	80.66	78.73	78.34
	Rotten	80.97	78.32	76.02	76.10
Horse	Fresh	91.45	90.43	88.91	88.28
	Frozen	89.60	88.89	86.21	86.80
	Rotten	87.24	86.91	84.54	84.02
Fork	Fresh	93.46	86.32	89.64	86.21
	Frozen	80.59	84.27	82.31	82.11
	Rotten	83.33	82.63	80.04	80.70
Average:		**87.42**	**85.81**	**83.32**	**83.26**

Meanwhile, the performance of Coiflets and Symlet is almost the same, but still lower than Haar and Daubechies.

Fresh meat condition produces the highest extraction value compared to frozen and rotten conditions. This shows that the texture structure of fresh meat is easier to recognize than the texture of meat that has been frozen or rotten. In addition, the test results also show that certain types of meat, such as horse meat and pork, have a texture that is easier to identify with high extraction results, especially in the fresh category. In contrast, lamb meat showed the lowest extraction results in all categories, indicating a greater challenge in recognizing its texture.

4.2 Texture analysis of meat images using GLCM

Testing with GLCM was conducted to analyse the texture of meat images based on various types of meat, namely beef, buffalo, lamb, horse, and pork. Each type of meat was tested in three different condition categories: fresh, frozen, and rotten. This approach aims to evaluate the ability of GLCM to extract meat texture features based on a co-occurrence matrix that considers the spatial relationship between pixels in the image. In this scenario, the main parameters calculated using GLCM include several texture features, namely, Energy (EY), Contrast (CO), Correlation (CR), Homogeneity (H), and Entropy (EN)

Meat images were taken from each type and category, then processed to produce GLCM features at certain angles (0°, 45°, 90°, 135°) with certain pixel distances. The results of this feature extraction are used to compare how the texture of each type of meat is affected by different conditions. This test is expected to provide insight into the unique texture patterns of each type of meat, so that it can be used for classification purposes. Table 3 below shows the results of feature extraction using GLCM.

From the feature extraction results presented in Table 3 using GLCM at an angle of 0°, an analysis of five texture features can be carried out, namely Energy (EY), Contrast (CO), Correlation (CR), Homogeneity (H), and Entropy (EN). In general, the Energy value ranges from 0.6954 to 0.8021 with an average of 0.7463, indicating that meat with a more homogeneous texture has a higher value, such as Pork, fresh meat which has the highest value (0.8021). Conversely, Lamb Rotten meat has the lowest Energy value (0.6789), indicating a more varied texture. For contrast, the value which measures texture irregularity ranges from 10.65 to 19.11 with an average of 14.683. Fresh pork had the lowest Contrast value (10.65), indicating a more homogeneous texture, while Lamb Rotten had the highest Contrast value (19.11), and indicating greater irregularity.

The Correlation feature measures the relationship between adjacent pixels, values ranged from 0.8574 to 0.9345, with an average of 0.9028. Fresh pork had the highest Correlation value (0.9345), indicating a close relationship between pixels, while Lamb Rotten had the lowest Correlation value (0.8574), indicating a weaker relationship between pixels. Homogeneity measures the uniformity of pixel distribution, values ranged from 0.8045 to 0.8921, with an average of 0.8490. Fresh pork had the highest Homogeneity value (0.8921), indicating a very uniform distribution, while Lamb Rotten had the lowest Homogeneity value (0.7989), indicating irregularity in pixel distribution. Finally, on the Entropy feature, which describes the irregularity or complexity of the image, the values ranged from 1.1987 to 1.5342, with an average of 1.3599. Fresh pork had the lowest Entropy value (1.1987), indicating less irregularity, while Lamb Rotten had the highest Entropy value (1.5342), indicating greater variation in texture.

Table 4 shows the results of feature extraction using GLCM for the 45° angle.

Based on the feature extraction results that use GLCM at a 45° angle in Table 4, the analysis of the five texture features showed significant differences in texture characteristics between types and conditions of meat. Energy which indicates texture homogeneity, had the highest value in Fresh pork (0.8045), indicating a very homogeneous texture, while Lamb Rotten had the lowest value (0.6833), indicating a more varied texture. Contrast, which measures texture irregularity, also showed a striking difference, with Fresh pork having the lowest value (10.20), indicating a more uniform texture, and Lamb Rotten having the highest value (18.29), indicating greater texture irregularity.

In the Correlation feature, which measures the relationship between adjacent pixels, Fresh pork shows a stronger relationship between pixels with the highest value (0.9358), while Lamb Rotten has the lowest value (0.8581), indicating a weaker relationship between pixels. Homogeneity, which measures the uniformity of pixel distribution, shows that Fresh pork has a very uniform distribution with the highest value (0.8905), while Lamb Rotten has the lowest value (0.7968), indicating a more irregular pixel distribution.

Table 3. Feature extraction results using GLCM (Angle 0°)

Type of Meat	Category	GLCM				
		EY	CO	CR	H	EN
Beef	Fresh	0.7823	12.34	0.9231	0.8745	1.2075
	Frozen	0.7564	14.67	0.9045	0.8423	1.3161
	Rotten	0.7121	16.89	0.8867	0.8156	1.4547
Buffalo	Fresh	0.7645	13.21	0.9178	0.8632	1.2894
	Frozen	0.7342	15.45	0.8943	0.8327	1.3995
	Rotten	0.6954	18.02	0.8712	0.8045	1.5123
Lamb	Fresh	0.7431	14.12	0.9102	0.8523	1.3102
	Frozen	0.7156	16.34	0.8825	0.8257	1.4231
	Rotten	0.6789	19.11	0.8574	0.7989	1.5342
Horse	Fresh	0.7954	11.89	0.9289	0.8834	1.2103
	Frozen	0.7682	13.76	0.9134	0.8556	1.3294
	Rotten	0.7256	15.98	0.8912	0.8264	1.4405
Fork	Fresh	0.8021	10.65	0.9345	0.8921	1.1987
	Frozen	0.7794	12.89	0.9210	0.8654	1.3156
	Rotten	0.7412	14.92	0.9048	0.8423	1.4234
Average		**0.7463**	**14.683**	**0.9028**	**0.8490**	**1.3599**

Table 4. Feature extraction results using GLCM (Angle 45°)

Type of Meat	Category	GLCM				
		EY	CO	CR	H	EN
Beef	Fresh	0.7982	13.56	0.9262	0.8701	1.2204
	Frozen	0.7634	15.21	0.9056	0.8410	1.3407
	Rotten	0.7186	17.32	0.8854	0.8135	1.4587
Buffalo	Fresh	0.7695	12.98	0.9193	0.8617	1.2803
	Frozen	0.7391	14.99	0.8951	0.8304	1.3980
	Rotten	0.7018	17.43	0.8718	0.8036	1.5111
Lamb	Fresh	0.7480	13.89	0.9125	0.8507	1.3045
	Frozen	0.7204	15.87	0.8832	0.8232	1.4205
	Rotten	0.6833	18.29	0.8581	0.7968	1.5330
Horse	Fresh	0.7991	11.32	0.9300	0.8852	1.2058
	Frozen	0.7719	13.43	0.9142	0.8541	1.3241
	Rotten	0.7283	15.57	0.8927	0.8275	1.4402
Fork	Fresh	0.8045	10.20	0.9358	0.8905	1.1950
	Frozen	0.7810	12.32	0.9215	0.8643	1.3140
	Rotten	0.7440	14.58	0.9054	0.8419	1.4231
Average		**0.7484**	**14.79**	**0.9027**	**0.8495**	**1.3637**

Finally, Entropy, which describes the complexity or irregularity of texture, shows that Fresh pork has the lowest value (1.1950), indicating a more regular texture, while Lamb Rotten has the highest value (1.5330), indicating a more complex variation in texture. Overall, Fresh pork shows a more homogeneous and regular texture, while Lamb Rotten shows a more irregular and complex texture.

Table 5 shows the feature extraction results for the 90° angle.

Table 5. Feature extraction results using GLCM (Angle 90°)

Type of Meat	Category	GLCM				
		EY	CO	CR	H	EN
Beef	Fresh	0.7834	13.45	0.9241	0.8752	1.2403
	Frozen	0.7582	14.60	0.9051	0.8431	1.3520
	Rotten	0.7153	16.72	0.8860	0.8175	1.4635
Buffalo	Fresh	0.7672	13.05	0.9185	0.8612	1.2815
	Frozen	0.7375	15.34	0.8938	0.8321	1.3925
	Rotten	0.6984	17.49	0.8723	0.8042	1.5140
Lamb	Fresh	0.7461	14.00	0.9115	0.8521	1.3084
	Frozen	0.7192	16.15	0.8839	0.8243	1.4237
	Rotten	0.6819	18.42	0.8564	0.7983	1.5345
Horse	Fresh	0.7988	11.80	0.9292	0.8845	1.2101
	Frozen	0.7710	13.60	0.9133	0.8560	1.3220
	Rotten	0.7251	15.79	0.8917	0.8287	1.4415
Fork	Fresh	0.8032	10.90	0.9353	0.8912	1.1973
	Frozen	0.7801	12.45	0.9208	0.8665	1.3158
	Rotten	0.7403	14.75	0.9041	0.8412	1.4239
Average		**0.7454**	**14.73**	**0.9025**	**0.8442**	**1.3524**

Table 6. Feature extraction results using GLCM (Angle 135°)

Type of Meat	Category	GLCM				
		EY	CO	CR	H	EN
Beef	Fresh	0.7834	12.12	0.9235	0.8750	1.2632
	Frozen	0.7560	14.25	0.9045	0.8400	1.3780
	Rotten	0.7125	16.85	0.8862	0.8130	1.4578
Buffalo	Fresh	0.7643	13.05	0.9180	0.8600	1.2855
	Frozen	0.7321	15.30	0.8939	0.8300	1.3960
	Rotten	0.6950	17.20	0.8700	0.8020	1.5125
Lamb	Fresh	0.7425	13.45	0.9115	0.8510	1.3120
	Frozen	0.7150	15.50	0.8830	0.8240	1.4210
	Rotten	0.6780	18.10	0.8560	0.7980	1.5330
Horse	Fresh	0.7948	11.78	0.9290	0.8840	1.2080
	Frozen	0.7685	13.60	0.9130	0.8550	1.3280
	Rotten	0.7250	15.70	0.8915	0.8270	1.4410
Fork	Fresh	0.8015	10.15	0.9355	0.8915	1.1990
	Frozen	0.7790	12.50	0.9215	0.8640	1.3155
	Rotten	0.7410	14.80	0.9050	0.8420	1.4235
Average		**0.7465**	**14.27**	**0.9027**	**0.8492**	**1.3655**

Based on the results of feature extraction using GLCM for a 90° angle in Table 5, it can be analysed that the condition of the meat affects each extracted feature. For the Energy (EY) feature, the average value is 0.7454, which indicates the level of regularity of the image texture. Fresh meat tends to have a higher Energy value, indicating a more consistent texture, while rotting meat shows a lower Energy value due to its more varied texture. The Contrast (CO) feature, with an average of 14.73, measures the difference in pixel intensity, where rotting meat shows a higher Contrast value, reflecting a rougher and more non-uniform texture. Conversely, fresh and frozen meat has lower Contrast values, indicating a smoother texture.

For Correlation (CR), which averages 0.9025, fresh meat shows stronger and more regular pixel-to-pixel relationships, with the highest value in Fresh Beef. Rotting meat, with a more irregular texture, has a lower Correlation value. Homogeneity (H), with an average value of 0.8442, describes the uniformity of the image texture. Fresh meat generally has a higher Homogeneity value, indicating a smoother and more uniform texture, while rotting meat has a lower Homogeneity value. Finally, the Entropy (EN) feature, with an average of 1.3524, measures the irregularity in the image texture. Rotting meat shows a higher Entropy value, reflecting a more complex and chaotic texture, while fresh meat has lower Entropy, indicating a more regular texture.

Table 6 shows the feature extraction result for 135° angle.

Based on the feature extraction results using GLCM for an angle of 135° in Table 6, there are several patterns that can be identified related to the condition and type of meat. For the Energy (EY) feature, the average value of 0.7465 indicates that fresh meat tends to have a higher Energy value, reflecting a more regular and consistent texture, while rotting meat shows a decrease in Energy value, indicating a more irregular and more complex texture. Contrast (CO), with an average of 14.27, shows the difference in intensity between pixels. Higher Contrast values are found in rotting meat, meaning the texture becomes rougher and more contrasting, while fresh meat has a lower Contrast value with a smoother texture.

In Correlation (CR), with an average of 0.9027, fresh meat shows a stronger relationship between pixels with higher values, indicating a more regular and uniform texture. Rotting meat has a lower Correlation value, indicating a more random and unorganized texture. Homogeneity (H), with an average value of 0.8492, measures the uniformity of the image texture. Fresh meat tends to have higher Homogeneity values, while rotting meat has lower Homogeneity values, indicating irregularity in its texture structure. Finally, Entropy (EN), with an average value of 1.3655, measures the degree of irregularity in the image texture. Rotting meat generally has higher Entropy values, indicating a more complex and chaotic texture, while fresh meat shows lower Entropy, reflecting a more regular texture.

Overall, the results of GLCM feature extraction at 135° angle show that meat condition affects the texture properties of the image that can be measured through parameters such as Energy, Contrast, Correlation, Homogeneity, and Entropy. Fresh meat tends to have more consistent values in these parameters, while rotting meat shows higher values in Contrast and Entropy, and lower in Energy and Correlation, indicating a more irregular and rougher texture. This indicates that the GLCM technique at 135° angle can be effectively used to distinguish the quality and condition of meat based on image texture.

4.3 Feature fusion

In the combination of Wavelet and GLCM, features from both methods are combined to obtain a more complete description of image texture. Wavelet provides frequency information at various scales, while GLCM describes the spatial relationship between pixels based on intensity values. The combination of both can identify more texture details in the image and improve the model's ability to distinguish image classes in the analysis of fresh, frozen, and rotten meat quality. In this context, the merging process is carried out using early fusion. Table 7 shows the results of combining the two Wavelet and GLCM methods.

Table 7. Results of combining the feature extraction methods (Wavelet and GLCM)

Type of Meat	Category	Wavelet Coefficients			GLCM					Combined Features
		Horizontal	Vertical	Diagonal	EY	CT	CO	H	EN	
Beef	Fresh	0.7823	0.7564	0.7121	0.7868	12.86	0.9242	0.8737	1.2140	0.7823, 0.7564, 0.7121, 0.7868, 12.86, 0.9242, 0.8737, 1.2140
	Frozen	0.7564	0.7342	0.6954	0.7585	14.68	0.9049	0.8416	1.3467	0.7564, 0.7342, 0.6954, 0.7585, 14.68, 0.9049, 0.8416, 1.3467
	Rotten	0.7121	0.6954	0.6789	0.7155	16.94	0.8861	0.8149	1.4587	0.7121, 0.6954, 0.6789, 0.7155, 16.94, 0.8861, 0.8149, 1.4587
Buffalo	Fresh	0.7645	0.7342	0.6954	0.7664	13.07	0.9184	0.8615	1.2842	0.7645, 0.7342, 0.6954, 0.7664, 13.07, 0.9184, 0.8615, 1.2842
	Frozen	0.7342	0.7156	0.6789	0.7357	15.27	0.8943	0.8313	1.3965	0.7342, 0.7156, 0.6789, 0.7357, 15.27, 0.8943, 0.8313, 1.3965
	Rotten	0.6954	0.6789	0.6256	0.6977	17.54	0.8713	0.8036	1.5125	0.6954, 0.6789, 0.6256, 0.6977, 17.54, 0.8713, 0.8036, 1.5125,
Lamb	Fresh	0.7431	0.7156	0.6780	0.7449	13.87	0.9114	0.8515	1.3088	0.7431, 0.7156, 0.6780, 0.7449, 13.87, 0.9114, 0.8515, 1.3088
	Frozen	0.7156	0.6789	0.6534	0.7176	15.97	0.8832	0.8243	1.4221	0.7156, 0.6789, 0.6534, 0.7176, 15.97, 0.8832, 0.8243, 1.4221
	Rotten	0.6789	0.6534	0.6123	0.6805	18.48	0.8570	0.7980	1.5337	0.6789, 0.6534, 0.6123,

										0.6805, 18.48, 0.8570, 0.7980, 1.5337
Horse	Fresh	0.7954	0.7682	0.7256	0.7970	11.70	0.9293	0.8843	1.2086	0.7954, 0.7682, 0.7256, 0.7970, 11.70, 0.9293, 0.8843, 1.2086
	Frozen	0.7682	0.7256	0.7156	0.7699	13.60	0.9135	0.8552	1.3259	0.7682, 0.7256, 0.7156, 0.7699, 13.60, 0.9135, 0.8552, 1.3259
	Rotten	0.7256	0.7186	0.6534	0.7260	15.76	0.8918	0.8274	1.4408	0.7256, 0.7186, 0.6534,
Fork	Fresh	0.8021	0.7794	0.7412	0.8028	10.48	0.9353	0.8913	1.1975	0.8021, 0.7794, 0.7412,
	Frozen	0.7794	0.7412	0.7156	0.7799	12.54	0.9212	0.8651	1.3152	0.7794, 0.7412, 0.7156, 0.7260, 15.76, 0.8918, 0.8274, 1.4408
	Rotten	0.7412	0.7186	0.6776	0.7416	14.76	0.9048	0.8419	1.4235	0.7412, 0.7186, 0.6776, 0.7416, 14.76, 0.9048, 0.8419, 1.4235

Based on Table 7, the results of combining the Wavelet and GLCM feature extraction methods produce a more complete data representation, allowing for more accurate separation of meat categories. The increasing entropy value in the rotten category indicates significant texture degradation, while the higher energy value in fresh meat reflects a more regular texture structure. This shows that feature fusion method is effective in analyzing texture images for the classification of meat types and conditions.

4.4 Classification with k-NN

The classification process using the k-NN algorithm begins by utilizing the combined feature data of the Wavelet and GLCM methods. This data includes wavelet coefficients (horizontal, vertical, diagonal) and texture features from GLCM (energy, contrast, correlation, homogeneity, and entropy). The first step is to standardize the data to ensure the same scale. Next, the dataset is divided into training data and test data for performance evaluation. The k-NN model works by calculating the distance between the test data and the training data using a distance metric such as Euclidean. The value of k=3 is used, where the three nearest neighbors determine the class based on the majority. The classification results are evaluated using accuracy, precision, recall, and confusion matrix to measure model performance. This process aims to identify meat categories (fresh, frozen, rotten) with high accuracy based on the extracted features. Table 8 shows the results of meat texture classification using the k-NN method.

Based on Table 8, the results of meat texture classification using the k-NN method showed very good performance with an average overall accuracy of 97.2%. Classification was carried out on five types of meat, namely Beef, Buffalo, Lamb, Horse, and Pork, each of which is divided into three condition categories: Fresh, Frozen, and Rotten. The results show that Beef has a high level of accuracy, ranging from 98%-100%, with the model being able to distinguish the three categories consistently. Buffalo and Lamb meat showed an average accuracy of 96%-98%, although there were small errors in distinguishing the Frozen and Rotten categories. Horse meat had the highest level of accuracy, reaching 100% in almost all categories, indicating the model’s excellent ability to classify this type of meat. Meanwhile, Pork meat also showed high performance with an accuracy of 100% for the Fresh and Frozen categories, and a slight decrease in the Rotten category, with an accuracy ranging from 94%-98%.

Table 8. Results of meat texture classification using the k-NN method

Sample	Type of Meat															Accuracy (%)
	Beef			Buffalo			Lamb			Horse			Fork			
	Class			Class			Class			Class			Class			
	Fresh	Frozen	Rotten	Fresh	Frozen	Rotten	Fresh	Frozen	Rotten	Fresh	Frozen	Rotten	Fresh	Frozen	Rotten	
50	0	0	0	0	0	1	0	0	**49**	0	0	0	0	0	0	98
50	0	0	0	0	0	0	1	**49**	0	0	0	0	0	0	0	98
50	0	**49**	0	0	0	0	0	0	0	0	0	0	0	1	0	98
50	0	0	0	0	0	2	0	0	0	0	0	0	**48**	0	0	96
50	0	0	0	0	0	0	0	0	0	0	**50**	0	0	0	0	100
50	0	0	**48**	0	0	2	0	0	0	0	0	0	0	0	0	96
50	0	0	0	0	0	0	0	0	0	0	0	**50**	0	0	0	100
50	**50**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
50	0	0	0	0	1	0	0	0	0	0	0	0	0	**49**	0	98
50	0	0	0	0	0	0	2	0	0	**48**	0	0	0	0	0	96
50	0	0	0	0	0	0	**50**	0	0	0	0	0	0	0	0	100
50	0	1	0	**49**	0	0	0	0	0	0	0	0	0	0	0	98
50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**50**	98
50	0	0	0	0	0	**50**	0	0	0	0	0	0		0	0	100
50	0	3	0	0	**47**	0	0	0	0	0	0	0	0	0	0	94
								Average								**97.2**

Although the overall performance is very good, small errors in distinguishing Frozen and Rotten categories, especially in Buffalo and Lamb meat, indicate the similarity in texture between these categories. Potential improvements can be made by adding training data, adjusting the *k* parameters of k-NN, or using additional features to improve the separability between categories. In general, the k-NN method proved effective in classifying meat texture based on features extracted from Wavelet and GLCM, providing accurate and consistent prediction results.

In the context of this research, the main reason for distinguishing frozen and rotten meat is not only important from the technical perspective of image classification, but also has major implications for health, legal compliance, industrial efficiency, and public trust.

4.5 Evaluation

Confusion matrix is an important evaluation tool in assessing the performance of classification models [29-31]. One of them is the task of classifying meat texture based on fresh, frozen, and rotten categories as shown in Figure 3.

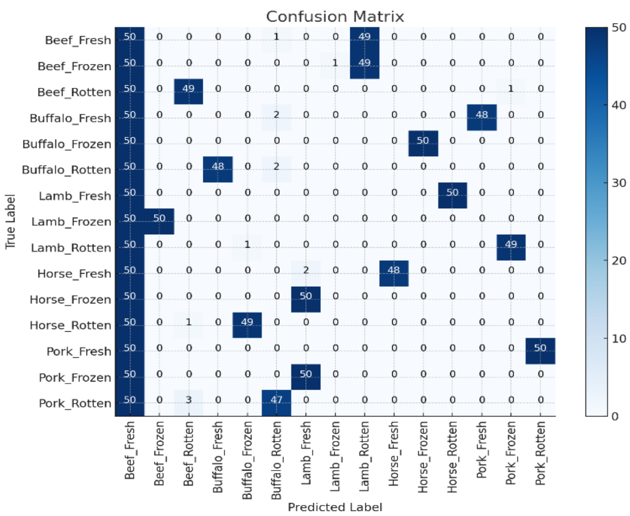

Figure 3. Visualization of confusion matrix

The evaluation process begins with the collection of meat texture data that has been extracted using the Wavelet and GLCM methods. The resulting features are used as input for the k-NN model. The dataset is divided into training data to develop the model and testing data to evaluate the predictions. The k-NN model then predicts the category of each sample based on the nearest distance of the neighbors in the feature space. Then, the prediction results are compared with the actual labels to construct a confusion matrix, which shows the number of correct predictions (True Positives and True Negatives) and prediction errors (False Positives and False Negatives) for each category.

5. CONCLUSION

Evaluation of the combined Wavelet and GLCM model for texture feature extraction of various types of meat images shows the effectiveness of the integration of these two techniques. Wavelet transform excels in capturing spatial-frequency features, while GLCM effectively represents texture patterns through statistical relationships of pixel intensities.

The research results showed that this hybrid approach significantly improved the ability to distinguish different meat categories (fresh, frozen, and rotten) across different types of meat, including beef, buffalo, lamb, horse, and pork. The combined model achieved an average classification accuracy of 97.2% using the k-NN method, indicating its robustness and reliability in feature extraction and classification tasks.

In addition, based on the analysis results, it was found that the wavelet coefficients provide complementary information with the statistical texture features of GLCM, thereby increasing the separation between classes in the feature space. Evaluation using a confusion matrix confirmed the reliability of the model, with most predictions being in the correct category, although there were some misclassifications due to overlapping feature characteristics in several categories.

For future research, it is recommended to explore the use of more sophisticated classification models, such as Support Vector Machines (SVM), Random Forest, or even deep learning-based approaches such as Convolutional Neural Networks (CNN), which have been shown to be able to identify complex patterns in images with high performance.

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