Fat Content, Color and Texture Features for Fresh Meat Evaluation from Digital Image

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***Abstract*—** In meat quality evaluation, some parameters can be used as a benchmark such as meat freshness, fat content, and meat tenderness. The physical properties of meat can be seen visually by human eye. The meat freshness can be measured by meat and fat color. Likewise, fat content parameter that can be seen from the spread of fat or called as marbling. Then meat tenderness which is reflected the nature of meat texture. Therefore, computer vision can be used to analyze meat without damaging the physical properties of meat itself. This study uses two colors image space, i.e. RGB and HSV to inspect the brightness level of meat. Red, Green, Hue, and Saturation layer have high correlation values more than 0.8 with the brightness of meat color by expert judgment. To analyze physical properties of marbling has been used volumetric (area) and distances its distribution (spatial). Area and spatial large fat have higher correlation with fat marbling by expert than other sizes. For texture features, two approaches have been used, which are spatial and texture transformations. As the result, texture transformation with Wavelet produce correlation values higher than the spatial approach Gray Level Co-Occurrence Matrix.

***Keywords*—** fat content, glcm, meat freshness, meat tenderness, meat quality evaluation, wavelet transform.

I. Introduction

In determining the grade of meat, especially beef ordinary villagers and researchers have used a variety of methods. Analysis of meat manually by experts is the most widely used method, but this method has many shortcomings because basically human nature that is easily tired, bored, and the lack of a level of accuracy. Besides of that, the food experts have created a tool that is combined with chemicals so that they can see the levels of fat, protein, and water from the meat. Although it has a high accuracy (over 99%), these tools require the meat to be destroyed first and then mixed with chemicals to detect pregnancy. Then there is a tool for calculating the tenderness of meat that Warner-Bratzler. It works by cutting the meat was boiled at a temperature of 70, 80, and 90 °C with a speed of 40 mm/sec. The result is the required power to press the tool to cut the meat in one kg/cm^2. It is impossible to apply in the fresh food production. So it takes a device or method that can provide color, marbling fat, and texture information for a piece of meat, so that it remains fit for consumption.

Then it has developed various methods of mechanics based on computer vision, such as that developed by Hassen et al. [1], two types of ultrasound to determine the fat content in the meat. Antequera et al. [8] used magnetic resonance imaging (MRI) and Fulladosa et al. [3] used Computed Tomography (CT) to assess the texture of the meat. Of course, these tools take a long time to work and too expensive. So it takes the development of green computing technologies that are able to keep working durability (consistent), objective and efficient.

Several techniques have been developed based on computer vision as well, but only used a simple camera as an image capturing and some segmentation methods in its processing. One that has been developed is by Widiyanto et al. [9], with a cluster-based segmentation methods produce accuracy levels of up to 92-94%. However, these methods were applied to the ham (pork). In addition to determine the level of quality meat based solely on marbling of fat, not based on color and texture. By way of, the same validation expected number of attributes that more can provide higher accuracy in predicting the quality of the meat.

Based on the description above, this study contributes in predicting the grade of a meat and provides detailed information such as the level of fat marbling, color brightness, and texture of the meat. Information obtained in real time to the seller (packaging) and information is easily accessible to buyers, such as can be seen in the packaging directly.

II. Methods

A. Data and Material

In acquisition process, stable condition data is required to retrieve information repeatedly with a predetermined period of time. The environment that supports or light intensity should be constant is also importance, so that there is no shift in pixel value. Therefore, in this study the treatment of meat is very important for acquisition process. The acquisition is the result of expert consultation to slaughterhouses.

The meat is taken from the Rib, or what is known in meat quality inspection, which is part of Longissimus Dorsi. Furthermore, the meat is secured for six hours at room temperature. If the meat is directly inserted into the machine chiller (cooling), there will be damage on muscle tendon meat. Chilling process itself was carried out for 24-48 hours, so that

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if the meat brought into normal temperatures has time to make the meat stays fresh.

After the chilling process has been completed, followed by removing the meat to room temperature for two hours. The data is obtained through the image acquisition process by using a DSLR camera and Digital microscope embedded inside a black box and coupled with LED lamp for illumination mode. The black box is used to reduce interference environmental light and LED lamp serves as a producer of light with uniform intensity. The full setup of the image acquisition tools can be seen in Figure 1. The images result from a digital camera in addition to be used as input data also as ground truth data for manual segmentation by meat expert.

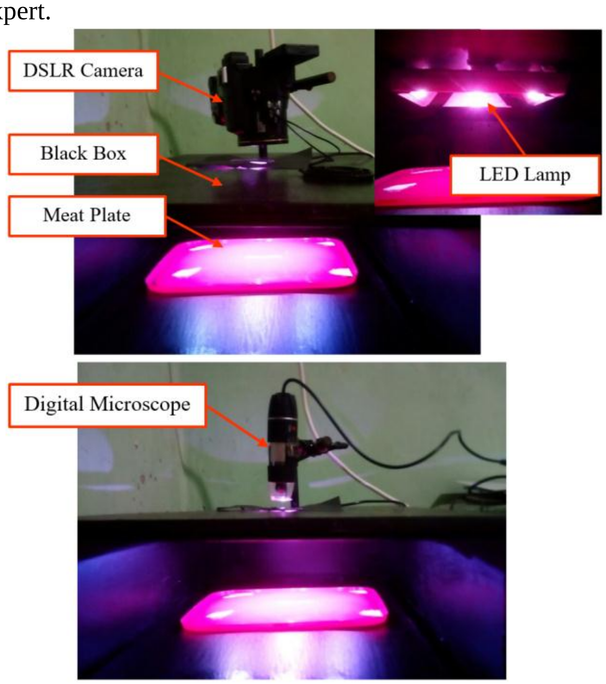

Fig. 1: Image Setup image acquisition device. Left: with digital camera, right: with a digital microscope.

The next process is the measurement of color and marbling level by experts using a comparison tool and color marbling score. While slightly different from the measurement ground truth for texture features, first way is through the ability of experts in meat to determine the texture of meat based on visualization and the second should be brought to the laboratory processing of meat Bogor Agriculture University to be tested level of tenderness using tool Warner Bratzler. The overall feature's measurements are based on meat quality standards published by the Indonesian National Standard Organization with registration number SNI 3932:2008 [5]. It can be seen in Table 1. Vulnerable period during the spending process outside from a chiller, only allowed a maximum of four hours to maintain the level of freshness of meat.

TABLE I:
MEAT QUALITY STANDARDS BASED ON SNI 3932: 2008

No.	Type of Test	Quality Requirements		
		I	II	III
1.	Meat Color	Bright Red Score 1 - 5	Rather Dark Red Score 6 - 7	Dark Red Score 8 – 9
2.	Marbling	Score 9 - 12	Score 5 - 8	Score 1 – 4
3.	Texture-Tenderness	Smooth-Tender (< 5 kg/cm^2)	Mid-Tender (5 – 7.56 kg/cm^2)	Tough (> 7.56 kg/cm^2)

B. *Application Development*

This research was conducted on development of applications to extract fat content, color and surface texture features of the meat's image. There are two stages in image processing is preprocessing and extraction.

Preprocessing: Image Quality Enhancement

The preprocessing is an operation in image processing to improve image quality and provide reliable data for further processing. A piece of beef containing noise and have parts that are not needed in the primary process.

Noise the image can be reduced or removed using the low-pass filter, the Gaussian filter (1). Low-pass filter is to eliminate the values that are too high in the image (smoothing). These filters are non-iterative, local, simple, and based on the spatial domain [2]. Gaussian has size parameter windows, such as 15 x 15.

$$H(x,y) = e^{-\frac{D^2(x,y)}{2\sigma^2}} \tag{1}$$

where *x* is the distance between pixels in the horizontal axis, *y* is the distance between pixels in the vertical axis, and σ is the standard deviation of a Gaussian distribution.

The next preprocessing eliminates unneeded areas, for example, is the background. Background removal can be done with Stien et al. [10] methods, that use the global threshold for sorting meat filet of salmon with background (packaging containers). This method focuses on a layer of Red, Green, and Blue (RGB), which according to Widiyanto et al. [9] the meat area has a value of intensity at higher layers of the Red, Green, and Blue. If the pixel (*x, y*) is the image of a meat, then the following formula, meat and background areas can be separated (2).

$$\alpha(x,y) = \begin{matrix} 1 & R(x,y) > G(x,y) \cap R(x,y) > B(x,y) \\ 0 & otherwise \end{matrix} \tag{2}$$

if $\alpha(x,y)$ equal to 1, the indicated pixel (*x, y*) is the area of meat, and if 0 is indicated as a background.

Image Feature Extraction

Once the image is obtained, which has better quality, the image will be extracted using methods that can produce marbling, color, and texture feature. These features are inspected through the segmentation and 3D modeling to determine marbling and fat percentage. To get the color feature, lean meat area is used. The area was analyzed using the attributes associated with color features and statistics, such as mean, standard deviation and covariance of RGB and HSV image. Then, grayscale image is used to get texture features by applying GLCM and wavelet Symlet8.

Marbling Feature Extraction

In the stage of marbling feature extraction, image segmentation method is used to separate the fat in beef. Segmentation method to be used is Bias Corrected Fuzzy C-Means (BFCM) to be modified specifically for the purposes of image segmentation meat. This is because this method was originally intended human brain segmentation that was introduced by Ahmed et al. [4]. Ahmed also modified algorithm that is essentially Fuzzy C-Means. In BFCM is possible to eliminate non homogeneity surface of the meat, which is often caused by noise and aging. Homogeneous image can be used to determine the average existing of meat color. This is necessary, as it uses color features as one of the parameters in the grading of meat.

BFCM uses a Gaussian kernel to repair the intensity of the meat. BFCM algorithms work to find clusters that depend on the centroid value determined in advance as a central of the cluster. In this research, the centroid is defined for the three clusters. The first centroid is used to define the background, with a fat content centroid to two, and the last centroid to identify lean area.

After a successful segmentation, the next process is to measure the marbling contained in the meat. Jackman et al. [7] used the intensity value from segmentation results (white or 1) as fat. Bringing the sum of pixels equal to 1 is the amount of fat contained in the meat. To retrieve a presentation of the fats in meats is by dividing the total number of pixels with pixel regions that contain fat meat. This way is quite effective, but not represent the nature of the fat inside the meat. Fat basically has irregular geometric shapes. Based on these studies, the fat has a form of cylindrical geometry with a constant altitude. Therefore, Widiyanto et al. [9] developed a method for analyzing the geometric shape of fat and model it in 3D. The model was built using the normalization function of the distance transformation (3).

$$D_{T_{Norm}} = \frac{\sqrt{d_x^2+d_y^2}}{\max\left(\sqrt{d_x^2+d_y^2}\right)} \tag{3}$$

Based on range value of the normalization transformation, fat volume can be estimated by indicating the value of *h* as constant, because *h* as the maximum thickness of the meat. Therefore, the thickness of the fat will not exceed the thickness of the meat (4).

$$V_{A_i} = \sum\sum D_{T_{Norm}} \times h \tag{4}$$

where A_i is the area of the fat region, and DT is the distance value of normalization transformation. All step in estimating fat volume can be seen in Figure 2.

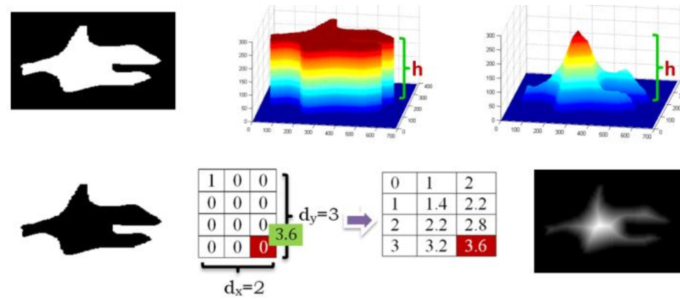

Fig. 2: Image Process volume estimate based on the normalized distance transformation.

a) image segmentation results; b) methods of representation fat, Jackman et.al. (2010); c) methods of representation fat, Widiyanto et. al. [9]; d) image inversion; e) the calculation of the distance transformation; f) volume models.

In determining fat distribution Widiyanto et al. [9] analyzed the types of fat that has high correlation with the percentage of fat. By measuring the density, size, and shape of fat as a sub parameter of marbling features.

Color Feature Extraction

To predict the level of meat quality, one can use the color feature. Color is the result from the perception of light in the visible spectrum region, and has a wavelength between 400nm up to 700nm. While the color space is an abstract mathematical model that describes a color that can be represented as rows of numbers usually with the values of three or four colors or components. This study used two-color spaces are RGB and HSV. By default, image acquisition results using digital tools to produce RGB images (Red, Green, Blue). Then RGB image color space is converted to the HSV (Hue, Saturation, Value) to add the color feature (5) (6) (7).

$$H = \tan\left(\frac{3(G-B)}{(R-G)(R-B)}\right) \tag{5}$$

$$S = 1 - \frac{\min(R,G,B)}{V} \tag{6}$$

$$V = \frac{R+G+B}{3} \tag{7}$$

Furthermore, by these two-color spaces have been obtained three statistical features that mean, standard deviation, mean of covariance.

Texture Feature Extraction

One of the methods used to obtain texture feature is Wavelet transforms, which is more efficient in extracting features from meat texture [6]. Wavelet transformed is the sum of the original signal waveform that is multiplied by the shift and scale in a time domain. Wavelet has six types are quite well known, namely Biorthogonal, Coiflet, Daubechies, Dmey, Reverse-Biorthogonal, and Symlet. Symlet is better in dealing with the meat texture compared to other types.

Symlet produces 37 root mean square value of wavelet decomposition of the image resolution of 256x256. Initially, seven orders wavelet decomposition (2, 3, 4, 5, 6, 7, and 8) is used to measure the texture of the meat is not homogeneous. So that, 259 texture features are obtained and the average value calculated and divided by the standard deviation.

Other texture features are used such as contrast, correlation, energy, and homogeneity, which are obtained by Gray-Level Co-occurrence Matrix (GLCM). Contrast indicates local variations of the matrix gray-level co-occurrence. Then correlation shows the probability of the pair of pixels specified. The energy is sum of squared elements GLCM. Furthermore, it is known as the uniformity or second moment angle. Lastly, homogeneity measures the proximity of the distribution of elements in GLCM to value GLCM diagonal.

III. Results and Discussion

From the test results on marbling features found that vLB, v, P, and cLB have high correlation values (> 0.7 based on the best practice), i.e. 0.83, 0.75, 0.75, and 0.81 respectively. vLB is marbling that describes large volume and branching fat. v is the total volume in one pieces, while P is the percentage of fat volume with meat piece's volume. Then, cLB is a feature of the distribution amount of fat with large and branching characteristics. The complete results of the feature extraction marbling can be seen in Table 2.

The features used in color are RGB and HSV color space, combined with a statistical feature that are standard deviation, mean and covariance. From statistic result, covariance of Red layer has value of correlation is 0.86. Then Green layer for all the statistical data has correlation value 0.86, 0.83, and 0.84 respectively. While, the blue layer is completely unable to describe the color feature.

For HSV color space, Hue layer with statistical data indicates that mean and standard deviation have correlation values 0.72 and 0.91. Further, the standard deviation of Saturation layer has significant correlation value 0.98 and followed by correlation of covariance value 0.89. As for Standard Deviation has correlation value 0.79. The overall results are shown in Table 3.

TABLE II:
MARBLING FEATURE EXTRACTION RESULTS TABLE

Class * / Image	*Data Ground Truth* (Score)	features Marbling												
		Area Fat							Spreading fats					
		vLC	vLB	vMC	vMB	vS	v	p	cLC	cLB	cMC	cMB	cS	c
1/1	9	260 313	102 333	12	0	0	128 376	16:05	4	4	1	0	0	9
1/2	9	23 624	143 912	220	0	2359	170 117	21:26	30	2	20	0	2	54
1/3	10	1746	9303	73	0	200 250	292 372	36.55	7	2	7	0	2	18
1/4	9	48 085	75 182	213	0	1578	125 060	15.63	50	2	20	0	3	75
2/1	6	13571	10463	63	0	8524	32623	4:08	32	1	6	0	4	43
2/2	6	33 840	64 266	382	0	7314	105 804	13:23	80	1	36	0	7	124
2/3	6	6153	7543	162	0	5608	84 466	10:56	22	1	14	0	2	39
2/4	7	27 237	6390	169	0	20 529	54 326	6.79	69	2	15	0	10	96
3/1	4	17189	0	44	0	13307	30542	3.82	18	0	4	0	3	25
3/2	4	30 280	0	258	0	7381	37920	4.74	46	0	22	0	5	73
3/3	4	13130	0	21	0	0	13152	1.64	10	0	2	0	0	12
3/4	4	23 992	6616	128	0	311	31049	3.88	17	1	12	0	1	31
Correlation vs. Class Features		-0.38	**-0.83**	-0.06	NaN	-0.35	**-0.75**	**-0.75**	0.01	**-0.81**	-0.08	NaN	0073	-0.14

Note: v = Volume, L = Size big fat, M = Size of fat medium, S = Size of fat is small, B = fat with branching forms, c = Fat with a compact form, c = Total distribution of fat and P = Percentage of total fat keseluruan meat area.

TABLE III:
COLOR FEATURE EXTRACTION RESULTS TABLE

*Class * / Image*	*Data GT*	Features Color																	
		R			G			B			H			S			V		
		Std. dev	mean	cov	Std. dev	mean	cov	Std. dev	mean	cov	Std. dev	mean	cov	Std. dev	mean	cov	Std. dev	mean	cov
1/1	5	149.8	126.8	143.7	33.8	46.5	45.9	75.1	241.9	264.5	1.6	29.9	155.5	2.1	9.9	38.2	0.5	15.7	128.2
1/2	5	133.1	102.2	119.9	30.8	39.5	39.7	59.3	118.5	129.0	0.8	33.5	135.4	1.6	8.8	33.3	0.2	6.0	82.3
1/3	4	146.5	118.9	137.6	36.8	49.1	47.2	25.3	64.2	75.0	1.5	32.8	151.0	1.9	10.8	39.9	0.2	6.3	33.4
1/4	4	131.3	98.2	116.9	32.5	44.0	44.5	35.6	67.0	86.6	1.1	36.5	134.4	1.8	10.5	35.7	0.2	7.3	52.0
2/1	6	71.8	56.7	62.4	20.2	22.8	25.5	70.9	62.4	122.0	0.4	16.7	73.1	1.2	4.4	22.4	0.2	7.1	85.5
2/2	6	96.9	70.6	82.5	24.9	28.9	29.9	134.9	123.7	149.8	0.4	27.3	97.8	1.1	7.4	26.2	0.1	15.7	148.9
2/3	7	60.5	45.8	47.8	12.8	13.6	15.2	33.0	12:2	17.0	0.3	16.2	61.3	0.8	4.4	13.8	0.1	8.5	29.8
2/4	6	84.5	58.9	65.7	18.6	21.1	23.1	57.5	49.3	68.4	0.2	26.4	85.1	0.8	6.4	19.4	0.1	10.6	58.3
3/1	9	122.8	65.8	52.0	15.9	18.7	19.5	84.7	62.5	57.5	0.0	70.9	122.8	0:0	8.3	15.9	0.0	18.5	84.7
3/2	9	151.2	88.3	72.8	21.1	28.2	29.6	56.4	64.4	60.8	0.0	78.4	151.2	0.1	11.9	21.1	0.0	8.8	56.4
3/3	9	105.5	59.6	43.1	11.4	11.6	11.8	49.4	18.4	17.2	0.0	62.3	105.5	0.0	6.3	11.4	0.0	23.1	49.4
3/4	9	128.0	73.1	56.2	14.3	17.4	18.4	21.3	12.4	15.6	0.0	71.8	128.1	0.0	6.7	14.3	0.0	2.2	21.3
Correlation vs. Class Features		-0.18	-0.65	**-0.86**	**-0.86**	**-0.83**	**-0.84**	0:06	-0.56	-0.61	**-0.91**	**0.72**	-0.23	**-0.98**	-0.29	**-0.89**	-0.70	0:30	-0.23

In Table 4, the results for correlation between texture features with a value of shear force (kg/cm^2) are interpreted. Texture features used are contrast, energy, homogeneity, and all values wavelet decomposition. For GLCM features of a digital image camera correlation values 0.86, 0.78, and 0.86 respectively. As for the wavelet approximation, horizontal, vertical, and diagonal obtain a correlation score is 0.84, 0.86, 0.88, and 0.87. Slightly different for the analyzing of microscope image, for GLCM significant feature is the contrast and correlation features, namely 0.81 and 0.80. As for the wavelet features as well as the results of the digital image, correlation values that are significantly above 0.80.

TABLE IV:
TEXTURE FEATURE EXTRACTION RESULTS TABLE

Class * / Image	Data GT	Texture Image Camera Features								Microscope image Texture Features							
		Gray Level Co-occurence Matrix				Wavelet (Symlet8)				Gray Level Co-occurence Matrix				Wavelet (Symlet8)			
		Cont	Corr	Ener	Homo	cA	cH	cV	cD	Cont	Corr	Ener	Homo	cA	cH	cV	cD
1/1	1	2.0	0.9	0.1	0.7	83.4	10.4	11.7	4.9	1.4	0.9	0.02	0.7	80.9	6.1	7.0	6.5
1/2	1	2.0	0.8	0.1	0.7	71.3	10.7	13.6	5.0	0.6	0.9	0.05	0.8	79.7	4.2	4.5	3.8
1/3	1	2.3	0.9	0.1	0.7	88.4	9.8	10.6	4.2	1.1	0.9	0.03	0.7	84.2	5.4	5.7	6.0
1/4	1	1.7	0.8	0.1	0.7	79.0	9.3	10.4	4.1	0.7	0.9	0.06	0.8	67.3	5.0	4.3	4.8
2/1	2	0.6	0.8	0.2	0.8	43.3	6.1	7.9	2.7	1.6	0.9	0.04	0.7	116.0	11.6	9.5	10.9
2/2	2	1.0	0.8	0.2	0.8	54.3	8.8	9:5	3.7	1.8	0.9	0.05	0.7	126.7	11.8	9.9	11.7
2/3	2	0.3	0.2	0.3	0.9	26.0	3.8	4.3	1.6	0.8	0.9	0.17	0.8	101.5	7.0	5.9	6.7
2/4	2	0.5	0.8	0.2	0.8	39.4	6.0	5.5	2.3	0.8	0.9	0.16	0.8	90.1	7.2	6.1	7.1
3/1	3	0.3	0.9	0.3	0.9	34.7	4.6	3.8	1.7	3.6	0.9	0.06	0.6	125.4	21.7	14.7	15.7
3/2	3	0.8	0.9	0.2	0.8	50.9	6.3	5.8	2.7	2.2	0.9	0.15	0.8	100.5	16.5	11.5	11.6
3/3	3	0.2	0.8	0.3	0.9	22.5	2.8	2.8	1.2	5.1	0.8	0.04	0.6	139.7	24.5	17.6	18.1
3/4	3	0.4	0.8	0.2	0.8	32.3	3.5	4.8	1.6	4.1	0.8	0.09	0.6	124.3	20.8	15.6	15.7
Correlation vs. Class Features		**-0.86**	-0.02	**0.78**	**0.86**	**-0.84**	**-0.86**	**-0.88**	**-0.87**	**0.81**	**-0.80**	0.36	-0.51	**0.82**	**0.91**	**0.88**	**0.89**

Note: Cont = Contrast, Corr = Correlation, Ener = Energy, Homo = Homogeneity, cA = Approximation, cH = Horizontal, cV = Vertical, and cD = Diagonal.

IV. CONCLUSION

Meat quality evaluation based on marbling fat has significant value, especially fat that are large and branching. As for the color layer, for features Red, Green, Hue, Saturation, and Value have a high correlation above 0.8. Then, for contrast, energy, homogeneity, and all the features of wavelet provide significant correlation values above 0.7. These results indicate that there are possibilities for development such as improve texture feature extractor with regard to statistic feature used. The future work is the grading process using classification methods such as SVM or Deep Learning, which are already believed to be a powerful algorithm.

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