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Comparison of Performance According to Preprocessing Methods in Estimating %IMF of Hanwoo Using CNN in Ultrasound Images

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Abstract

There have been various studies in Korea to develop a %IMF(Intramuscular Fat Percentage) estimation method suitable for Hanwoo. Recently, a %IMF estimation method using a convolutional neural network (CNN), a kind of deep learning method among artificial intelligence methods, has been studied. In this study, we performed a performance comparison when various preprocessing methods were applied to the %IMF estimation of ultrasound images using CNN as mentioned above. The preprocessing methods used in this study are normalization, histogram equalization, edge enhancement, and a method combining normalization and edge enhancement. When estimating the %IMF of Hanwoo by the conventional method that did not apply preprocessing in the experiment, the accuracy was 98.2%. The other hand, we found that the accuracy improved to 99.5% when using preprocessing with histogram equalization alone or combined regularization and edge enhancement.

Keywords: *Preprocessing , Hanwoo, Ultrasound Images, CNN, %IMF(Intramuscular Fat Percentage)*

1. Introduction

In recent years, it is very important to preserve Hanwoo(Korean traditional cattle) with excellent meat quality in order to win the competition with relatively cheap imported foreign beef in Korea's livestock industry. The meat quality of Hanwoo is classified according to various factors [1, 2]. Among them, the most important criterion for judging high-quality meat is marbling [3-5]. Here, the marbling is determined by %IMF (Intramuscular Fat Percentage) and the distribution status of the intramuscular fat [6-8]. It is known that the method using an ultrasound image is the most suitable as a method for evaluating the marbling of live Hanwoo, that is, living body.

The most representative methods for evaluating marbling in ultrasound images are texture analysis methods made based on programming. It is very difficult to directly estimate the marbling score using this texture analysis method. Therefore, it is common to use the method of analyzing %IMF instead of directly estimating the marbling score. The reason is that the marbling score and %IMF have a very high correlation with each other.

There have been various studies in Korea to develop a %IMF estimation method suitable for Hanwoo [6, 7]. Recently, a %IMF estimation method using a convolutional neural network (CNN), a kind of deep learning method among artificial intelligence methods, has been studied [9]. In this study, ultrasound images obtained from 60 steers were used to estimate the %IMF. In order to make a learning process of CNN, which

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is a kind of supervised learning, after slaughtering steer, the real %IMF values obtained through chemical analysis of intramuscular fat are classified into 10 classes. And the total number of ultrasound images used in the experiment is 4909 ROI (region of interest) images of 80×80 size. Of these, 75% (3681 images) were used as training data and 25% (1228 images) were used as data for %IMF estimation tests. The CNN model used in this method consists of three convolution layers and two dense layers, that is, a fully connected layer (FCL).

Ultrasound images are inherently noisy, and when a rigid region is encountered in the course of ultrasound, a shadow is generated behind the rigid region and the texture is difficult to see [10]. In the ultrasound image, the rigid region is displayed brightly and the other areas are displayed relatively dark. In Hanwoo ultrasound image, the rigid region corresponds to the intramuscular fat region. According to the distribution of intramuscular fat in Hanwoo ultrasound image, the brightness value and standard deviation of the image change a lot locally. Therefore, in order to improve the performance of CNN, pre-processing that equalizes the image quality is absolutely necessary.

In this study, performance comparison was performed when various preprocessing methods were applied to %IMF estimation in ultrasound images using CNN as mentioned above. The preprocessing methods used in this study are normalization, histogram equalization, edge enhancement, and a method combining normalization and edge enhancement [11, 12]. Normalization converts ultrasound images with different characteristics into images with the same mean and standard deviation. Histogram equalization converts the probability distribution function of an image into a uniform distribution, and improves the image contrast by expanding the change range of the brightness value in the image, especially in the dark area. Edge enhancement is a method that emphasizes the boundary of an object. In this study, it helps to easily estimate %IMF by strengthening the boundary between the intramuscular fat region and the non-fat region. It is difficult to equalize the characteristics of the ultrasound images used in the experiment only with edge enhancement, so it is more efficient to use it in combination with normalization. When estimating the %IMF of Hanwoo by the conventional method that did not apply preprocessing in the experiment, the accuracy was 98.2%. The other hand, it was confirmed that the accuracy was improved to 99.5% when histogram equalization alone or preprocessing combining normalization and edge enhancement was used.

2. The Previous CNN Method

Figure 1 shows how to estimate Hanwoo's %IMF using the conventional CNN model in ultrasound images [9]. The conventional CNN model shown in Figure 1 consists of three convolution layers and two dense layers.

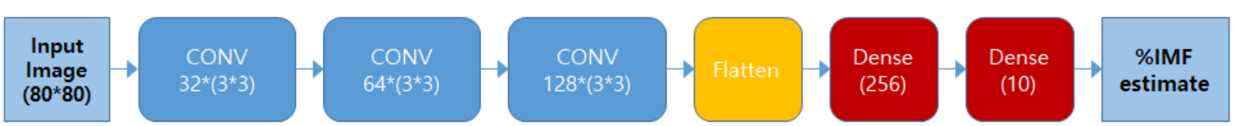


Figure 1. Block diagram of the previous CNN method

In Figure 1, the input ultrasound image first passes through the three-step convolution layer, then is converted into one-dimensional data, and then passes through the two-step dense layer to estimate the final %IMF. At this time, the number of neurons in the first dense layer was 256, and in the second step, 10 neurons were used to classify the %IMF values into 10 classes.

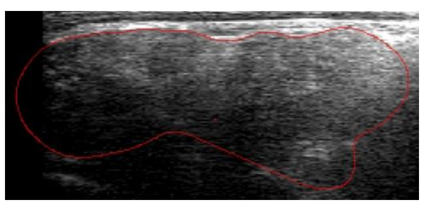
The size of the image used in the CNN model is 80×80. Dozens of 80×80 ROI images are obtained from a single steer. Because ultrasound images have strong local characteristics, 80×80 ROI images obtained from the same steer have different characteristics depending on the acquired location. If the %IMF can be accurately estimated from the ROI image with strong local characteristics obtained from various locations, it can be determined that this method can estimate the %IMF regardless of the skill level of the user who sets the ROI. The previous CNN model consists of a three-stage convolution layer and a two-stage dense layer (FCL: fully connected layer). The size of the filters used in each convolution layer is 3×3, and the number of filters is 32, 64, and 128, respectively.

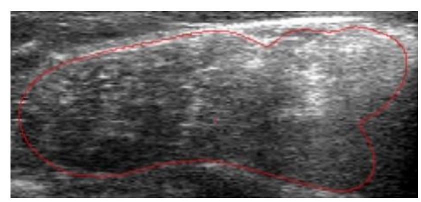
In the figure, each convolutional layer iteratively combines a convolution filtering, an activation function (ReLU), a max pooling, and a dropout. In addition, the number of convolution filters used in each convolutional layer was increased by a factor of 2 to construct a convolutional layer. The reason is to try to balance the system by designing a small number of filters in the layer near the input with a large image size, and increasing the number of filters as the image becomes smaller, that is, farther away from the input. In this way, the computation time and amount of computation of each step are relatively kept constant.

In this method, dropouts are placed on every layer to prevent overfitting. The role of dropout is to prevent learning biased by the training data by randomly turning off neurons as the neural network learns. In general, when learning data using a CNN, overfitting may occur if the number of features is large and the number of samples used for training is relatively small. In the case of %IMF estimation of Hanwoo, a dropout layer must be provided because the number of Hanwoo used in the experiment is relatively small and the number of ROI image samples to be obtained is also limited.

3. Preprocessing Methods

The process of analyzing %IMF in the ultrasound image of Hanwoo is to analyze the distribution and ratio of bright areas (regions containing intramuscular fat) in the ultrasound image. These intramuscular fat regions are visually differentiated by the presence of borders and differences in brightness values from the surrounding regions. Figure 2 shows three ultrasound images with different %IMF. The red line in the Figure 2 is the area where samples are usually taken to estimate the %IMF.


(a)


(b)

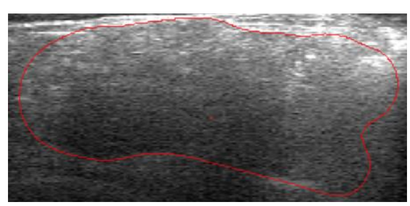

(c)

Figure 2. Ultrasound images with different fat percentage (a) fat percentage(%IMF = 7.22%); (b) fat percentage(%IMF = 9.79%); (c) fat percentage(%IMF = 14.17%)

As can be seen from the figure, each image has different brightness values and contrasts. When comparing Figure 2(a) and 2(b), it can be judged that the image with high %IMF has greater brightness and contrast, but the opposite case is shown when Figure 2(b) and 2(c) are compared. This difference in images shows that not only the difference in %IMF but also the characteristics of images vary according to various conditions when acquiring images.

In addition, due to various characteristics occurring in the process of acquiring an ultrasound image, a process different from that of a general image is required. Ultrasound images are inherently noisy, and when a rigid region is encountered in the course of ultrasound, a shadow is generated behind the rigid region and the texture is difficult to see [10]. In the ultrasound image, the rigid region is displayed brightly and the other areas are displayed relatively dark. In Hanwoo ultrasound image, the rigid region corresponds to the intramuscular fat region. According to the distribution of intramuscular fat in Hanwoo ultrasound image, the brightness value and standard deviation of the image change a lot locally. Therefore, in order to improve the performance of CNN, pre-processing that equalizes the image quality is absolutely necessary.

Therefore, in order to improve the %IMF estimation performance using CNN, factors other than fat content should be prevented from affecting the results as much as possible. As a solution, preprocessing is required to equalize the average and standard deviation of the brightness values of the input images and to emphasize more the judgment factors necessary for distinguishing the fat and non-fat regions.

The process of extracting features to be input to the deep learning dense layer in CNN is the convolution layer. This process is the same as the filtering process of traditional image processing. The image normalization method is the most representative method for making the brightness value and standard deviation of an image uniform so that various images inputted in image processing filtering can be compared under the same conditions. And in order to extract features well, histogram equalization and edge enhancement are methods to enhance the contrast and enhance the edges in the image [11, 12]. In this study, we compare and analyze the effect on %IMF estimation performance when this traditional preprocessing method is efficiently applied to CNN. Figure 3 shows the process of applying preprocessing to the previous CNN model. In Figure 3, the input image is first preprocessed and then processed by the CNN model. This preprocessing improves the feature extraction performance of CNN model.

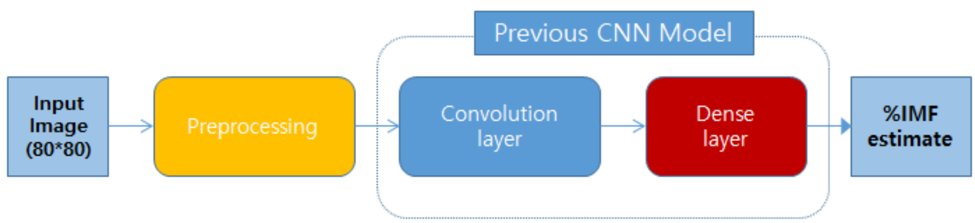


Figure 3. Block diagram with preprocessing applied to the previous CNN method

3.1. Normalization

Normalization is used to match the characteristics of multiple images input in various environments to the same condition as possible. In this case, the standard for making the same condition is to match the mean and standard deviation of the image. Normalization is the process of changing the range of brightness values of all pixels in the image and is defined as follows.

$$v(x,y) = \{u(x,y) - u_{mean}\}\frac{v_{std}}{u_{std}} + v_{mean} \tag{1}$$

In Equation (1), u and v represent images before and after normalization respectively. u_{mean} and u_{std} are the mean and standard deviation of the original image before normalization, v_{mean} and v_{std} represent the mean and standard deviation after normalization. By setting v_{mean} and v_{std} to desired values, the range of ROI image brightness is adjusted.

Figure 4 shows the result of image normalization using Equation (1) for an arbitrary ultrasound image of Hanwoo. Figure 4(a) shows the original image, and Figure 4(b) is histogram of the image. Figure 4(c) is the preprocessed image, and Figure 4(d) shows the histogram of the preprocessed image. In Equation (1), when the desired mean $v_{mean} = 80$ and standard deviation $v_{std} = 50$ after normalization was set, it was confirmed that u_{mean}= 131.5 and $u_{std} = 39.7$ of the image before transformation became $v_{mean} = 79.7$ and$v_{std} = 49.7$, respectively. In the image and histogram of Figure 4, it can be visually confirmed that the brightness value of the whole image decreases and the contrast increases compared to Figure 4(a) in Figure 4(c), which was preprocessed.

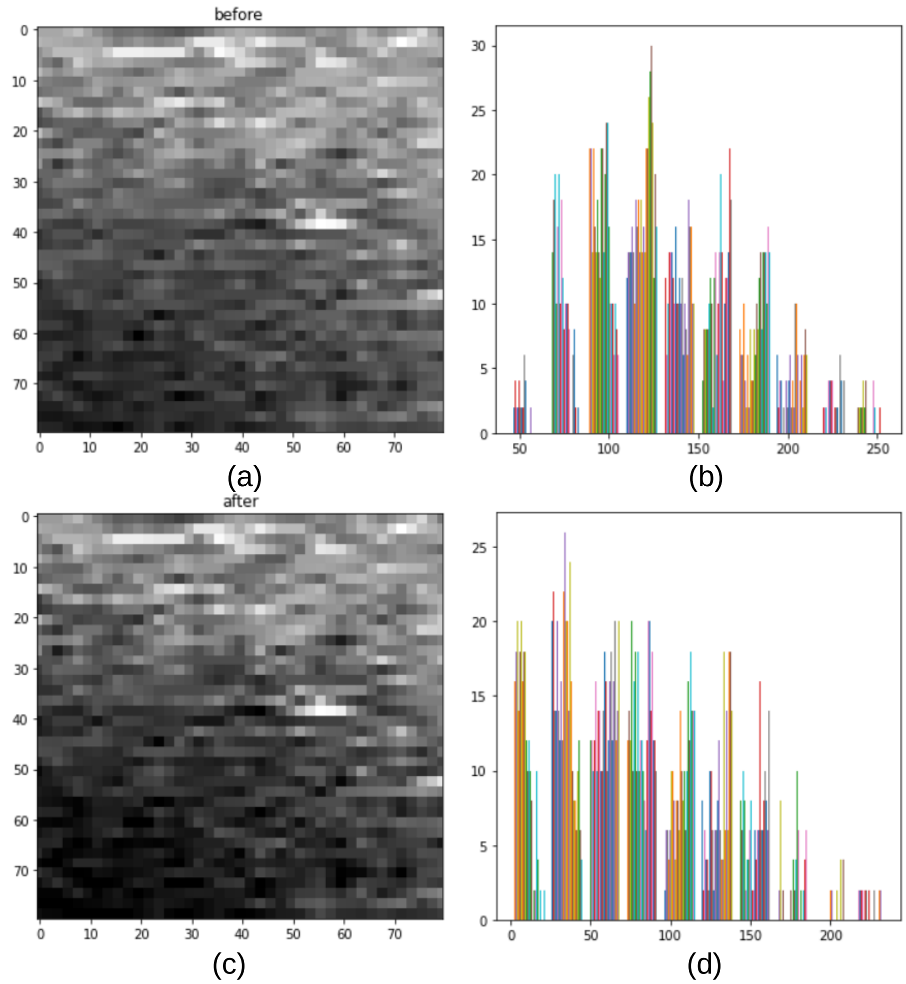


Figure 4. Comparison of the resulting image and histogram when normalization is performed on an arbitrary ultrasound image (a) original image; (b) histogram of original image; (c) preprocessed image; (d) histogram of preprocessed image

3.2. Histogram Equalization

The purpose of histogram equalization is to ensure that the image histogram has a uniform shape. This method is a preprocessing method that improves the image quality of images obtained in various environments and makes them have uniform characteristics. In particular, in the case of the ultrasound image of Hanwoo used in this study, histogram equalization is a very useful pre-processing method because the characteristics of the image vary greatly depending on the location of the ROI from which the sample is taken.

The implementation method of histogram equalization is as follows [11].

$$p_u(x) = \frac{h(x)}{\sum_{x=0}^{L-1} h(x)} \qquad x = 0,1, \ \ldots \quad , L-1 \tag{2}$$

$$\mathrm{v} \ \equiv \sum_{x=0}^{u} p_u(x) \tag{3}$$

$$v^* \ \equiv int\left[\frac{(v-v_{min})}{(1-v_{min})}(L-1)+0.5\right] \tag{4}$$

In Equation (2), $h(x)$ is the histogram of the input image u. In Equation (3), v is the histogram equalization transformed image. In Equation (4), v_{min} is the smallest value of v. $int[]$ is an integer uniform quantization. v^* is the histogram equalized result image.

Figure 5(a) is an image of the result of histogram equalization of arbitrary ultrasound images of Hanwoo in Figure 4(a), and Figure 5(b) is a histogram. In the figure, it can be seen that the distribution of the transformed image is definitely closer to the uniform distribution compared to the original image. If you look at the image resulting from histogram equalization, you can see that the contrast is clearly increased and the boundary of the object is clearly visible rather than the original image and histogram in Figure 4(a) and 4(b).

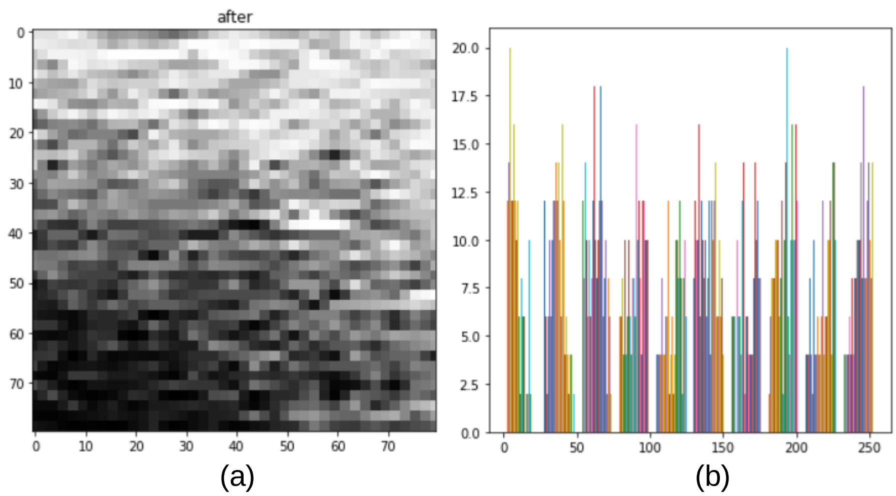


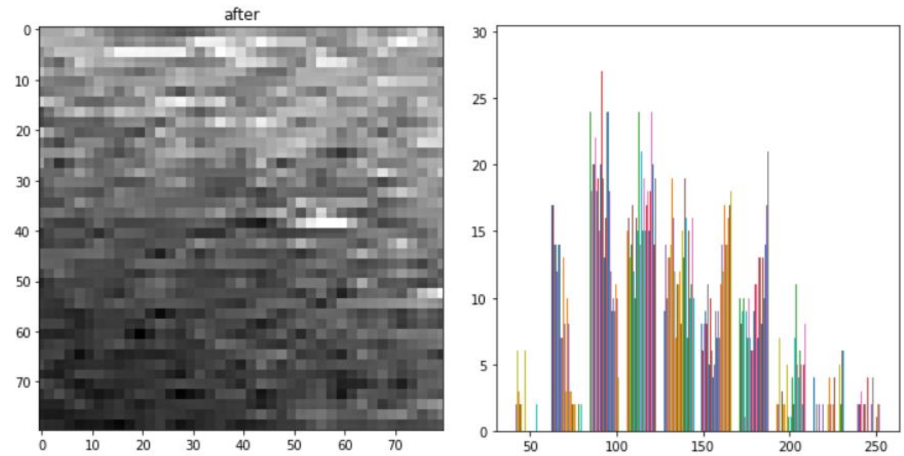
Figure 5. Resulting image and histogram when histogram equalization is performed on an arbitrary ultrasound image (a) preprocessed image; (b) histogram of preprocessed image

3.3. Edge Enhancement

Edge Enhancement is a preprocessing filter that emphasizes the boundaries of objects in the image so that objects in the image can be distinguished better. It is thought that it will be helpful to improve the %IMF estimation performance to clearly define the boundary between the fat and non-fat regions in Hanwoo ultrasound image. The process of performing edge enhancement is as Equation (5). In Equation (5), if the high-pass filtered image is multiplied by the weight λ and added to the original image, an image in which only the boundary of the object is emphasized can be obtained [12].

$$\begin{aligned} v(x,y) &= (\lambda+1)u(x,y) - \lambda h_{LP}(u(x,y)) \qquad \lambda > 0 \\ &= u(x,y) + \lambda(u(x,y) - h_{LP}(u(x,y))) \\ &= u(x,y) + \lambda h_{HP}(u(x,y)) \end{aligned} \tag{5}$$

In Equation (5), u and v represent images before and after normalization respectively. h_{LP} and h_{HP} denote low pass and high pass filters. λ is a weight value that sets how much edge to emphasize. Figure 6 is an image and histogram of the result of edge enhancement when $\lambda = 0.4$. Figure 6(a) is an image of the result of edge enhancement of arbitrary ultrasound images of Hanwoo in Figure 4(a), and Figure 6(b) is a histogram. In Figure 6, it can be seen that the boundary of the fat region of the image after preprocessing is somewhat emphasized compared to Figure 4(a). However, edge-enhanced images retain the mean and standard deviation of the original image in Figure 4(a).



(a) (b)

Figure 6. Resulting image and histogram when edge enhancement is performed on an arbitrary ultrasound image (a) preprocessed image; (b) histogram of preprocessed image

It is not suitable for the purpose of preprocessing to equalize images obtained in various environments. Therefore, in order to use this edge enhancement as a preprocessing process of CNN model, it is preferable to use it together with normalization, etc. rather than using it alone. In the figure, the intramuscular fat region, which is expressed as a bright value, is very small, so the effect of emphasizing the border is not conspicuous. It is expected that this method will work more efficiently in ultrasound images in which the intramuscular fat region has a certain size or more due to the higher resolution.

4. Results and Discussion

In this study, we tested how much performance change occurred only with or without preprocessing under the same conditions as the %IMF estimation method using the previous CNN model [9]. In the experiment, ultrasound images obtained from a total of 60 steers were used in the same manner as in the previous method. For each ultrasound image, the lumber (the longest muscle of the abdomen) between the 13th thoracic vertebra and the 1st lumbar vertebra on the left side of steer was taken. The actual %IMF measured chemically after the slaughter of a total of 60 steers used in the experiment ranged from 4 to 20.8%.

In this study, about 80 ROI images with a size of 80×80 were acquired as samples from the ultrasound images of steer. A total of 4909 80×80 ROI images obtained from a total of 60 steers were used for the experiment. Of these, 75% (3681 images) were used as training data and 25% (1228 images) were used as data for %IMF estimation tests. Since the ROI images were acquired at random locations at regular intervals without special prior knowledge, this method can easily estimate the %IMF even for non-specialists not related to the livestock industry. The previous CNN model used in the experiment was implemented using tensorflow and keras, a deep learning library provided by Python. Epoch, the number of times the backpropagation algorithm used in neural networks is applied to the entire data set, is set to 30.

Table 1 compares the performance when each preprocessor is applied to the previous CNN %IMF estimation method. The meaning of each column in Table 1 is explained as follows. The preprocessing method in the first column represents the preprocessing methods used in the experiment, and loss in the second column represents the loss function value in CNN. Accuracy in the third column expresses the proportion of predicted %IMF consistent with chemically analyzed %IMF.

Table 1. Comparison of %IMF classification performance by preprocessing method

Preprocessing method	loss	Accuracy
None(Previous method)	0.0841	0.9821
Normalization	0.0217	0.9943
Histogram equalization	0.0200	0.9951

Edge enhancement	0.0502	0.9902
Normalization + Edge enhancement	0.0363	0.9951

In Table 1, the prediction accuracy of the previous CNN model when no preprocessing is applied is about 98.2%. Looking at the performance with and without preprocessing, it can be seen that the case of applying preprocessing is generally superior. In particular, it can be seen that the performance is the best at 99.5% when histogram equalization is applied as a preprocessing and when a method combining normalization and edge enhancement is applied. This method combining normalization and edge enhancement contributes to performance improvement by supporting the efficient estimation of %IMF by making the image characteristics uniform and emphasizing the boundary where the intramuscular fat region and the non-fat region meet in the ultrasound image. Histogram equalization shows good results because the effect of emphasizing the boundary of an object can be obtained similarly to the method combining normalization and edge enhancement by improving the contrast in the image as a whole.

Due to the low resolution of the ultrasound image used in the current experiment, even small bright masses of intramuscular fat in the image are expressed. Therefore, the number of pixels corresponding to the intramuscular fat region boundary is not large. When the resolution of the ultrasound image is improved and the number of pixels corresponding to the intramuscular fat region boundary increases, the preprocessing method that combines normalization and edge enhancement is expected to show better %IMF estimation performance than when only histogram equalization is applied. The reason is that the edge enhancement effect of the method combining normalization and edge enhancement increases, and the parameter λ in Equation (5) can be appropriately adjusted according to the situation.

5. Conclusion

In this study, we compared the performance when various preprocessing methods were applied to the %IMF estimation method using CNN in ultrasound images. The preprocessing methods used in this study are normalization, histogram equalization, edge enhancement, and a method combining normalization and edge enhancement.

When estimating the %IMF of Hanwoo by the conventional method that did not apply preprocessing in the experiment, the accuracy was 98.2%. The other hand, it was confirmed that the accuracy was improved to 99.5% when histogram equalization alone or preprocessing combining normalization and edge enhancement was used.

In the future, if the resolution of the ultrasound image is improved and the number of pixels corresponding to the boundary of the fat region in the muscle increases, we expect that the preprocessing method combining regularization and edge enhancement will show better %IMF estimation performance than the method applying only histogram equalization.

Acknowledgement

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