Color and Texture Feature Extraction Using Gabor Filter - Local Binary Patterns for Image Segmentation with Fuzzy C-Means

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Abstract: Image segmentation to be basic for image analysis and recognition process. Segmentation divides the image into several regions based on the unique homogeneous image pixel. Image segmentation classify homogeneous pixels basedon several features such as color, texture and others. Color contains a lot of information and human vision can see thousands of color combinations and intensity compared with grayscale or with black and white (binary). The method is easy to implement to segemention is clustering method such as the Fuzzy C-Means (FCM) algorithm. Features to beextracted image is color and texture, to use the color vector L* a* b* color space and to texture using Gabor filters. However, Gabor filters have poor performance when the image is segmented many micro texture, thus affecting the accuracy of image segmentation. As support in improving the accuracy of the extracted micro texture used method of Local Binary Patterns (LBP). Experimental use of color features compared with grayscales increased 16.54% accuracy rate for texture Gabor filters and 14.57% for filter LBP. While the LBP texture features can help improve the accuracy of image segmentation, although small at 2% on a grayscales and 0.05% on the color space L* a* b*.

Keywords: Texture and Color, Image Segmentation, Local Binary Pattern, Gabor Filter, Fuzzy c-Means

1 INTRODUCTION

Interpret an image to obtain a description of the image through several processes including preprocessing, image segmentation, image analysis, and image interpretation (Perner, 2006). Image segmentation becomes a foundation for process analysis and image recognition. Segmentation divides the image into several regions based on the unique homogeneous image pixel (Gonzalez & Richard, 2002) (Raut, Raghuwanshi, Dharaskar, & Raut, 2009) and became a topic that is still widely studied (Cremers, Rousson, & Deriche, 2006). The purpose of segmentation is to separate the image into several regions so interpreted simply be something that is meaningful and easy to analyze.

Image segmentation classify homogeneous pixels based on several features such as color, texture and others. Color contains a lot of information and human vision can see thousands of color combinations and intensity compared with grayscale or with black and white (binary) (Cheng, Jiang, Sun, & Wang, 2001) (Khan, Adhami, & Bhuiyan, 2009). More complete information of color image and image segmentation is better compared with the scale of gray. The human visual system is not only able to distinguish objects based on color, but texture also has an important role.The texture of the image can be defined as a function of local spatial variation in pixel intensity and orientation on grayscale (Tuceryan & Jain, 1999). The main characteristics of the texture is a repeat pattern of spatial pixels in the image (Abbadeni, Zhou, & Wang, 2000) (Manjunath, Ohm, Vasudevan, & Yamada, 2001) which can be repeated exactly, or as a set of small variations, possibly as a function of position. By combining color and texture features of the image would be helpful in distinguish regions have the same color but different textures, or otherwise.

Approaches based on similarities and differences by Zaher Al Aghbari and Ruba Al-Haj (Aghbari & Al-Haj, 2006) image segmentation methods can be classified into five: threshold, boundary-based, region-based, clustering and combined or mixed methods.Of some of these methods apply the clustering method because it is easy to be applied and produce satisfactory segmentation results. The number of features characters from each image pixel as a vector space enter analyzed the clustering method so that it takes a preprocessing step to extracting features for each pixel. Clustering method that has been widely used, there are two main types of hard clustering and fuzzy clustering. Hard clustering (k-means) method which is simple and easy to use. However, in general a lot of issues such as limited spatial resolution, the minimum contrast, overlapping intensities, noise and intensity inhomogeneities reduce the effectiveness of hard clustering method (Krinidis & Chatzis, 2010). Algorithm fuzzy c-means (FCM) clustering method fuzzy one which gives the value of membership in each group for each pixel.

Feature extraction procedure resulted in a description of an object in terms of measurable parameters that represent relevant properties of the object, and can be used for classification by setting the object to the class (Vandenbroucke, Macaire, & Postaire, 2003). Image features are used for segmentation of color and texture features, although the nature of a separate feature which texture image uses level grayscale while color extracting all the information on the color space.Color is a feature in a three-dimensional color space (3D) RGB, which related to the frequency of the red, green and blue from the spectrum of light.In research Imtnan-Ul-Haque Qazi et al (Qazi, Alata, Burie, Moussa, & Fernandez-Maloigne, 2011) showed that the L* a* b* color space indicates the minimum correlation between luminance and chrominance information as well as the lesser of the color space used for color texture classification based on spatial structure information.

Then for feature extraction method on texture analysis in the past few years a lot of research analysis tektsur introduces Gabor filter method (Clausi & Jernigan, 2000) (Idrissa & Acheroy, 2002) (Zhang, Tan, & Ma, 2002) (Khan, Adhami, & Bhuiyan, 2009) because the cells in the visual cortex simple

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mammalian brain can be modeled by Gabor functions, so that image analysis by Gabor filter is similar to the human visual perception system.

Research that has combined a color and texture features is done by Khan (Khan, Adhami, & Bhuiyan, 2009) by applying a L* a* b* color space and Gabor filters. Gabor filter calculates pixel values to implement the filter banks on small neighborhoods that Gabor filters work well on macro texture and micro texture ignored. At the micro-textured images, Gabor filter performance in image segmentation becomes worse (Li & Staunton, 2008). To detect micro texture using Local Binary Patterns (LBP) (Mäenpää & Pietikäinen, 2006) which is based on research conducted by Ma Li and RC Staunton (Li & Staunton, 2008) and Lotfi Tlig et al (Tlig, Sayadi, & Fnaiech, 2012) in the color space grayscale.

This paper is organized as follows. In section 2, the related works are explained. In section 3, the proposed method is presented. The experimental results of comparing the proposed method with others are presented in section 4. Finally, ourwork of this paper is summarized in the last section.

2 RELATED WORKS

Research conducted by Ma Li and R.C. Staunton (Li & Staunton, 2008) a new approach to multi-texture image segmentation based on the formation of an effective texture feature vector with a color spacegrayscale. Vector texture features obtained from the integration between the single Gabor filter with local binary pattern (LBP). The method they propose to obtain a single Gabor filter becomes efficient for a small number of texture classes, but for three or more, can not distinguish the difference in texture. When integrated with LBP image segmentation for the better.

The research conducted by Jesmin F. Khan et al (Khan, Adhami, & Bhuiyan, 2009) an approach to new method of selection scale based on local image properties related to changes in brightness, color, texture and position are taken for each pixel at the selected size with L * a * b *color space. Feature image is measured using a Gabor filter in accordance with the selected adaptive orientation size frequency, and phase for each pixel. To cluster pixels into different regions, the joint distribution of pixel features is modeled by a mixture of Gaussians utilizing three variants of the expectation maximization algorithm (EM). Three different versions of EM used in research with clustering are: (1) Penalized EM, (2) Penalized stochastic EM, and (3) the inverse Penalized EM. Researchers determine the value of the number of models that best suits the natural number of clusters in the image based on the Schwarz criterion, which maximizes the posterior probability of the number of groups given the samples of observation.

Research conducted by Lotfi Tlig et al (Tlig, Sayadi, & Fnaiech, 2012) for texture analysis using Gabor filter which has been widely applied, but Gabor filter has a strong dependence on a number of parameters that affect the performance of texture characterization. Furthermore, Gabor filters can not extract texture features micro also has a negative effect on the clustering process. The approach taken in this study combines the outputs of grating cell operator (GCO) is derived from Gabor filters with local binary pattern (LBP).

In this research, we applying the feature extraction using Gabor filter-LBP as research conducted by Ma Li and RC Staunton (Li & Staunton, 2008) and and Lotfi Tlig et al (Tlig, Sayadi, & Fnaiech, 2012) for image segmentation based on color and texture features that have been proposed by Jesmin F. Khan (Khan, Adhami, & Bhuiyan, 2009).

3 PROPOSED METHOD

We propose a method for extracting color and texture features using Gabor filters -LBP are applied to the data for image segmentation research that secondary data drawn from the Berkeley Segmentation Dataset (BSDS).

The BSDS is a RGB image that will converted to L* a* b* color space, so it has three values L, a and b. From these values represent the values of L grayscale color space to extracting texture feature while the values of a and b represent the color feature.

For macro texture will be extracted using Gabor filters with a formula such as:

$$G_{\lambda\theta\varphi\sigma\gamma}(x,y) = e^{-\frac{\acute{x}^2+\gamma^2\acute{y}^2}{2\sigma^2}} \cos\left(2\pi\frac{\acute{x}}{\lambda}+\varphi\right)$$

$$\acute{x} = x\cos\theta + y\sin\theta$$

$$\acute{y} = -x\sin\theta + y\cos\theta$$

where Lambda (λ) is the wavelength parameters of the sinusoidal factor. λ is the inverse of the frequency of the wave in the Gabor function with a value of f = 1 / λ. Tetha (θ) is the normal orientation of the parallel lines of Gabor function, its value is determined in degrees between 0 and 360. Phi (φ) is the phase offset as a factor in the cosine Gabor function, its value in degrees between -180 and 180 Sigma (σ) standard deviation of the Gaussian factor determines the size of the (linear) support of the gabor function. σvalue can not be determined directly but can be changed only through the value of the bandwidth (b). Gamma (γ) is the spatial aspect ratio that determines the shape of the ellipse of the Gabor function. To γ = 1, the shape is a circle. To γ<1 elongated shape seen in the orientation function.

For micro texture will be extracted using Local Binary Patterns (LBP)witha formula such as:

$$LBP_{P,R}(x,y) = \sum_{P=0}^{P-1} s(g_P - g_C) * 2^P$$

$$s(x)\begin{cases}1\,; x \geq 0\\ 0\,; x < 0\end{cases}$$

where gp the neighboring pixels are evenly distributed sample points on the circle a number of P pixels with radius R centered at gc the center pixel.

Integrating the extraction of Gabor filters - LBP and color component a* and b* to be the image features which used as image attributes in clustering using fuzzy c-means (FCM).

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} U_{ij}^{w} \left\|x_i - v_j\right\|^2$$

As shown in Figure 1, the final image segmentation result is obtained from the measures proposed model.

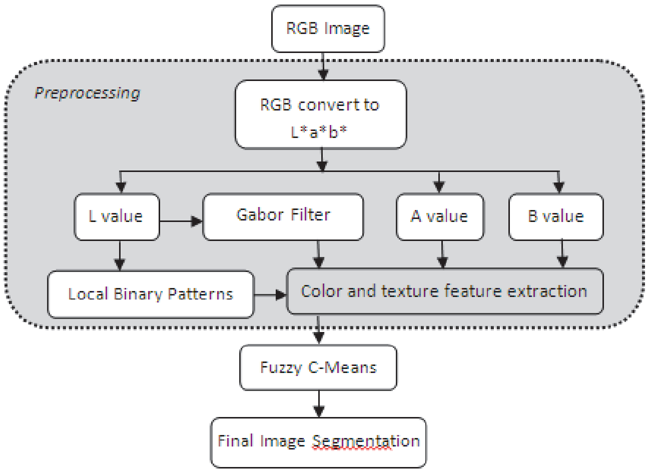

Figure 1.Proposed Method

Evaluation of the proposed algorithm with quantitative performance, where segmentation accuracy is estimated using hit rate (Khan, Adhami, & Bhuiyan, 2009). Hit rate is percentage number of pixels classified correctly compared to ground truth data. Ground truth data is label-segmentation of the human hand, which divides the image into some number of segments, where the segments representing parts of the image.

$$hit\ rate = \frac{number\ of\ pixels\ classified\ correctly}{number\ of\ pixels\ ground\ truth}\ x\ 100\%$$

4 EXPERIMENTAL RESULTS

Experiments and testing the proposed methods using Matlab R2012a. The data has been prepared and separated between training and testing data on preprocessing.

In the first experiment will be the process of transformation to sRGB color models from color space RGB, sRGB to CIE XYZ, CIE XYZ to CIE Lab as a color image extraction process. In this study, using the image processing toolbox of matlab for RBG color model transformation to the L * a * b * with the following command:

```
I_RGB = imread('317080.jpg');
cform = makecform('srgb2lab');
I_lab = applycform(I_RGB,cform);
```

Figure 2. Command Transformation CIE L*a*b* in Matlab

In the Figure 3 can be seen image after transformed from RGB color space to the color space L* a* b*. Taken value L* of the color space L* a* b* as representing the value luminace grayscale image is used for texture feature extraction.

Figure 3. BSDS image 317080 in RGB color space (left), transformation CIE L*a*b* (center) and value L* of CIE L*a*b*

In the process of texture feature extraction using Gabor filters, to build the filter bank must determine the parameters of Gabor functions, including:

a. Frequency (f)

Table 1. Frequency (f), lambda(λ) and sigma (σ)

F	λ	σ
0.18396	5.43590	3.05591
0.21751	4.59759	2.58464
0.23428	4.26846	2.39961
0.24266	4.12095	2.31668
0.24686	4.05096	2.27733
0.25314	3.95031	2.22075
0.25734	3.88595	2.18457
0.26572	3.76331	2.11563
0.28249	3.53989	1.99003
0.31604	3.16418	1.77881

b. Tetha (θ)
In this study using angle as suggested in (Clausi & Jernigan, 2000) are: (θ) = 0°, 30°, 60°, 90°, 120°, 150°

c. Phi (φ)=[0,90]

d. bandwidth (b)=1

e. Gamma (γ)=0.5

with the above parameters will result in the value of Gabor function (gb) which will be convoluted the original image (img) into a Gabor filter.

```
filgb = conv2(img, gb, 'same');
```

Figure 4. Command Convolution in Matlab

For the process of texture feature extraction using Gabor filter delivering sixty texture features. Texture features extraction with Gabor filter the value f = 0.18396, λ = 5.43590, σ = 3.05591 and θ = 0° after getting the value function and convolution with BSDS image as shown in Figure 5.

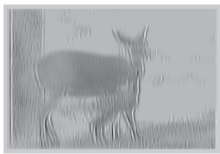

Figure 5. One of the Gabor filter texture feature extraction

On texture feature extraction using the Local Binary Pattern (LBP) using the L * value as the feature extraction with Gabor filters. L * value of 3 x 3 at BSDS image f (237,157) with the central pixel f (238,158) calculated the value of LBP 198.

Piksel 3 x 3

196	200	201
202	200	197
201	199	199

Threshold

0	1	1
1		0
1	0	0

Biner

1	2	4
128		8
64	32	16

pattern = 11000110
LBP = 2+4+64+128 = 198

Figure 6. Value LBP on BSDS image f (238,158)

To get the value of LBP texture features taken from the histogram by dividing the image blocks with size 3x3.

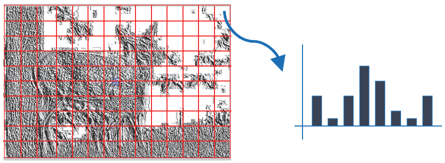

Figure 7. LBP texture feature extraction

Of the features that have been extracted, all combined to form a data vector with attributes, color features a* b*, texture feature using Gabor filters and texture feature using the LBP with records of 151686 pixels segmentation performed by Fuzzy C-Means (FCM).

In BSDS image is a natural image contains many colors and textures so many areas that can be formed in the image segmentation so that the number of clusters is determined two, three and four to produce a segmentation according to the ground truth object. Image segmentation with FCM using fuzzy toolbox in matlab with the command "fcm (data, number_of_clusters)".

Table 2. Data on color and texture features of the image BSDS

i	1	2	3	...	151684	151685	151686
a*	128	128	128	...	138	139	139
b*	128	128	128	...	159	159	158
Gb 1	0.60	0.60	0.61	...	0.47	0.48	0.49
Gb 2	0.43	0.43	0.44	...	0.27	0.24	0.24
...	...	...	...	...	...	...	...
Gb 59	0.51	0.50	0.50	...	0.44	0.59	0.59
Gb 60	0.41	0.41	0.40	...	0.57	0.59	0.52
LBP bn1	0	0	0	...	4	4	4
LBP bn2	3	3	3	...	0	0	0
...	...	...	...	...	...	...	...
LBP bn7	0	0	0	...	0	0	0
LBP bn8	6	6	6	...	1	1	1

Testing the model on the image BSDS by using the ground truth were correctly counted the number of pixels compared to the total number of pixels where the pixels were correctly marked with white color or value 1. From the calculations hit rate in the first experiment in Figure 8 the level of accuracy of 0.7968 (79.68%).

Figure 8. BSDS Image (top left), image segmentation (top right), ground truth (bottom left) and hit rate (bottom right)

In subsequent experiments carried out in the same way that the segmentation is determined using FCM to cluster two, three and four using color feature grayscale and L* a* b* and texture features Gabor filter and LBP.

Table 3. Experiments and testing models BSDS image

BSDS image	Cluster	Grayscale + Gabor	Grayscale + Gabor + LBP	L*a*b* + Gabor	L*a*b* + Gabor + LBP
317080	2	0.7968	0.7131	0.9582	0.9586
	3	0.5826	0.7490	0.8281	0.8235
	4	0.4908	0.6862	0.5372	0.5524
113016	2	0.5294	0.5208	0.9579	0.9522
	3	0.6484	0.6504	0.9781	0.9784
	4	0.6188	0.7029	0.9755	0.9753
12003	2	0.6855	0.7837	0.7820	0.7764
	3	0.8051	0.8144	0.8176	0.8187
	4	0.5283	0.3763	0.7936	0.7909
296059	2	0.8488	0.7137	0.7445	0.7433
	3	0.6808	0.8875	0.9808	0.9811
	4	0.5064	0.4820	0.6987	0.6007

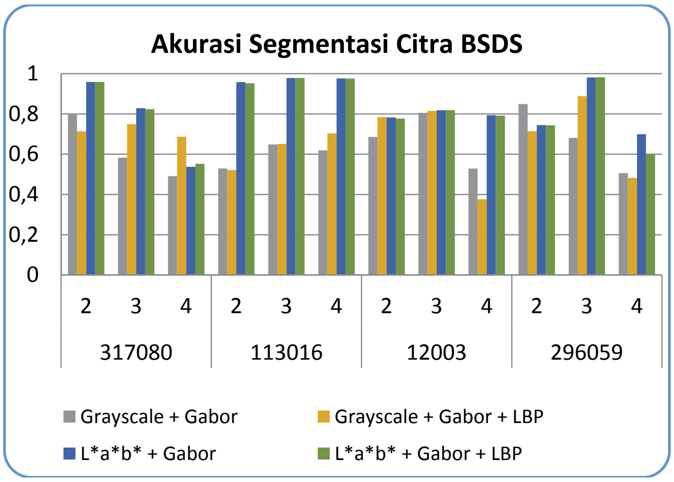

Figure 9. Graphical of accuracy BSDS image segmentation for each cluster

In testing the BSDS image is a natural image with a color features grayscale and the color space L* a* b* combined with texture feature Gabor filters and LBP, was tested on each cluster. Seen from Table 3 a comparison between the features and the cluster is shown in graphical form in Figure 9. Most of the number cluster is value four so levels accuracy to be decreases because the object was split to form a separate region with a central point adjacent to the pixels other than the object. To determine the improvement in the accuracy of each feature is used the highest accuracy value of each image for each feature because its object approaching the ground truth. Then averaged the accuracy of each feature of the image BSDS to each other than the accuracy of the segmentation of the features used in segmentation.

Table 4. The level of accuracy of BSDS image segmentation

Citra BSDS	Grayscale + Gabor	Grayscale + Gabor + LBP	L*a*b* + Gabor	L*a*b* + Gabor + LBP
317080	0.7708	0.7490	0.9584	0.9586
113016	0.6484	0.7029	0.9781	0.9784
12003	0.8051	0.8144	0.8176	0.8187
296059	0.8488	0.8875	0.9808	0.9811
Rata-rata	0.7683	0.7885	0.9337	0.9342

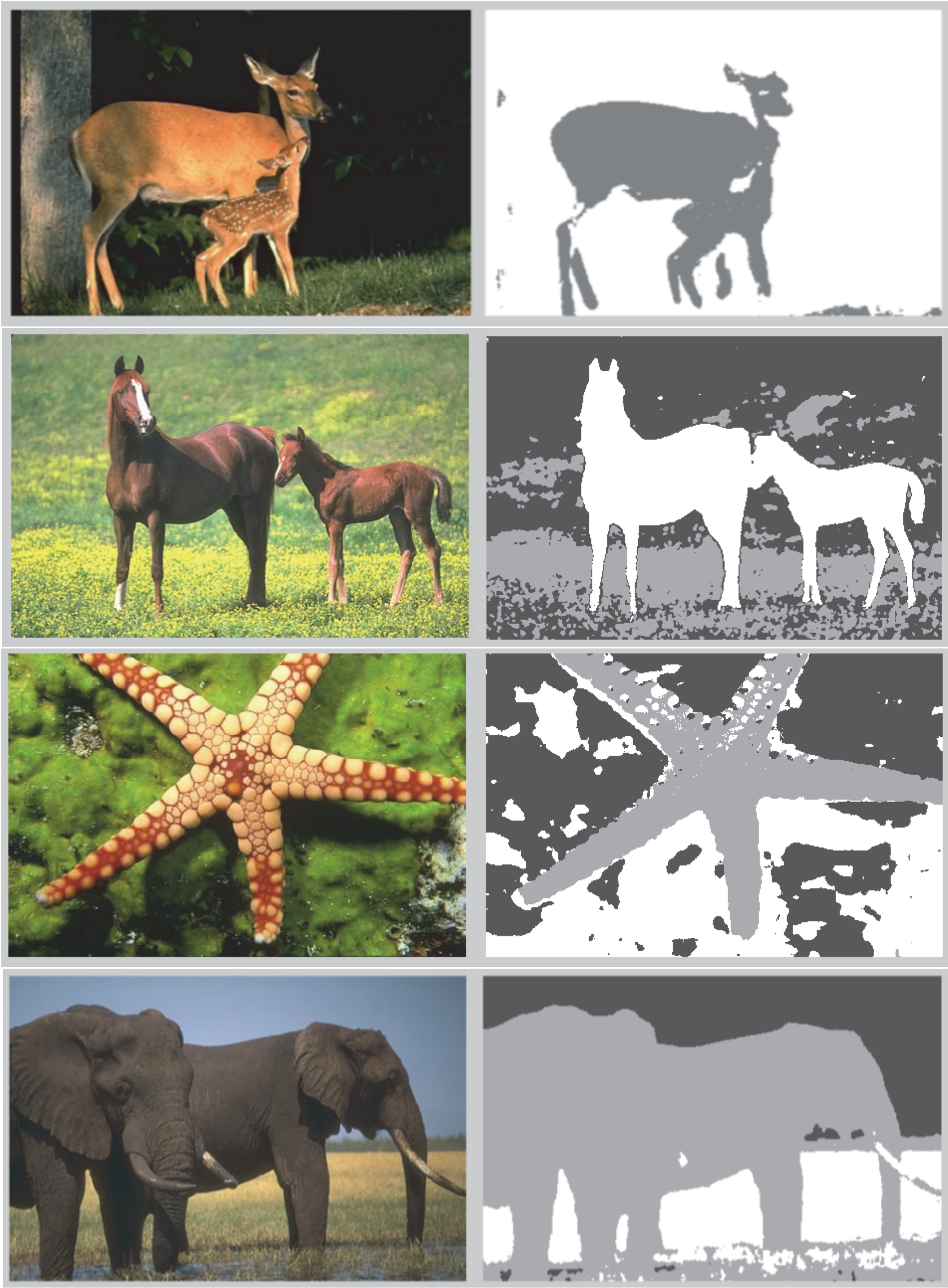

Figure 10. BSDS image (left) and segmentation has a high accuracy rate (right)

5 CONCLUSION

After conducting experiments and testing of BSDS image segmentation using FCM with applying color and texture feature extraction using Gabor filter-LBP then to the use of color features in comparison with the grayscale levels increased 16.54% accuracy for Gabor filter texture of 76.83% to 93.37 % and increased to 14.57% from 78.85% LBP filter becomes 93.42%. While the LBP texture features can help improve the accuracy of image segmentation by 2.02%, although small on color space grayscale from 76.83% to 78.85% and by 0.05% in the color space L* a* b* from 93.37% to 93.42%.

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