FUZZY LOGIC BASED FAULT CLASIFICATION OF INDUCTION MOTOR BEARING USED IN HOME WATER PUMP SYSTEM

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ABSTRACT

The water pump is a device for moving the water from a lower pressure to a higher pressure or a lower place to a higher place. The use of the water pump is still a lot of obstacles such as it does not remove the water, short circuit in the winding, and bearing failure. This paper discusses the development of fault bearing classification of induction motor (IM) used in home water pump system using fuzzy logic model. It is difficult to classify fault bearing of IM using a mathematical model. Thus, a fuzzy logic classification is employed in this matter. This classification is divided into four conditions such as all bearing normal (N), front bearing fault (F), rear bearing fault (R), and both bearing fault (B). Whereas, the classification process consists of three stages such as taking fault data, features extraction, and fuzzy logic fault classification. The data of bearing fault is obtained from the current of the water pump IM taken using soundcard oscilloscope software. For further process these data are changed from time domain into frequency domain using Fast Fourier Transform (FFT) to aquire more fault signs during features extraction. In this stage, 4 features fault bearing data are extracted. In last stage, fuzzy logic model is used to select and clasify fault bearing of IM. The robustness of proposes fuzzy logic model is examined and results of clasification for four bearing fault condition are shown.

Keywords: *Home Water Pump System, Bearing Fault, Fuzzy Logic, Fast Fourier Transform.*

1. INTRODUCTION

Water pump is used to easily work human, especially move water from a lower pressure to a higher pressure or a lower place to a higher place. The use of water pump in home appliance is still a lot of obstacles such as it does not remove the water, short circuit in the winding, and bearing failure. The bearing is one part of the induction motor (IM) components. It has the important function to reduce the friction occur in shaft of IM, so that the rotor of IM can be rotated. The bearings must be built from strong material to allow the shaft and other engine elements to work properly. Several tests of bearing condition have been conducted and developed to detect the bearing fault of induction motor [1-4]. However, it requires a complex mathematical model and expensive fault detection devices [2,4,5].

In this paper, fault classification of induction motor bearing is developed using fuzzy logic model. Purpose of this classification is to know bearing fault types and early detection of bearing failure on home water pump system. The fault types consist of four conditions such as all bearing normal (N), front bearing fault (F), rear bearing fault (R), and both bearings fault (B). While, the classification process consists of three stages such as taking bearing fault data, features extraction, and fuzzy logic fault classification. First stage, the data of bearing fault is obtained from current of the water pump IM taken using soundcard oscilloscope software v.1.41 through audio line input of personal computer [6]. In second stage, these data obtained from first stage are converted from time domain into frequency domain using Fast Fourier Transform (FFT) to aquire more fault signs during features extraction stage and than 4 features fault bearing data are extracted. In last stage, fuzzy logic model is used to select and clasify fault bearing of IM. The effectiveness of proposes fuzzy logic model is clarified by simulation using MATLAB. The results of clasification for four bearing fault condition are shown and concluded.

2. RESEARCH METHODOLOGY

The research methodology used to classify bearing failure of induction motor is shown in Figure 1. The bearing fault data used in this paper is obtained from the current of induction motor employed in home water pump system. The fault types consist of four conditions such as all bearing normal (N), front bearing fault (F), rear bearing fault (R), and both bearings fault (B).

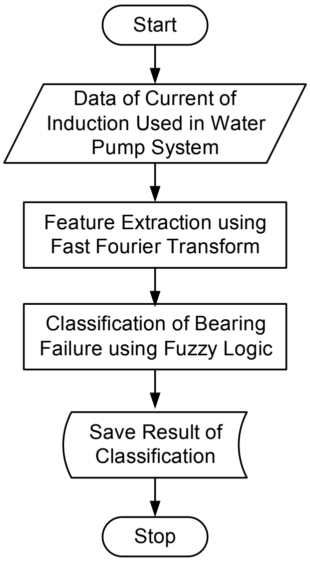

Figure 1. *Methodology to classify the bearing fault of induction motor*

In the feature extraction stage, bearing fault signal is converted from time domain to frequency domain using Fast Fourier Transform (FFT) to obtain more fault signals during features extraction and 4 features fault bearing data are extracted. Next stage, fuzzy logic model is used to select and clasify fault bearing of induction motor reffer to 4 bearing fault types.

2.1 Bearing of Induction Motor (IM)

Mechanical components of home water pump system are induction motor (IM), impeller, and foot valve. In the IM, the important mechanical component is bearing. Bearing is required to reduce friction at the shaft. Bearing fault can be caused over load, over heat, and corrosion [2,4]. Figure 2 show a bearing failure caused by corrosion.

Figure 2. *A Bearing fault caused by corrotion*

2.2 Fast Faurier Transform (FFT)

Frequency domain analysis used Fast Fourier Transform (FFT) method to convert from time domain into frequency domain. Frequency domain is used to show the frequency componets of a signal. Meanwhile, a time domain signal can be shown its time componets [1-3,6]. Formula of FFT for a signal *f(t)* can be expressed in Equation (1).

$$f(t) = \sum_{n=1}^{\infty} C_n \cos(n\omega t + \theta_n) \tag{1}$$

where c_n, $n\omega t$ and θ_n are magnitude of the nth component, frequency of the nth component, and phase angle of the nth component, respectively.

2.3 Fuzzy Logic Classification

Fuzzy logic is a system control method for problem solving which is suitable to be implemented into a system, from small systems to large and complex systems. This method can be employed to hardware, software, or a combination of both. In conventional logic, it states that everything is binary, meaning it has only two states, "yes or no", "1 or 0", and others. Therefore, the systems based on this logic have only a membership value of 0 or 1. Different on fuzzy logic control method, fuzzy logic control allows membership values to be between 0 and 1. This means that a situation may have two "Yes and No", "True and False" values, at the same time, but the value depends on the weight of the membership. Fuzzy logic control can be used in many fields [7-9] particularly classification and pattern matching of signals.

Block diagram of fuzzy logic control can be seen in Figure 3. Fuzzy logic control is built by fuzzification, inference mechanism, rule base, and defuzzification. Inference mechanism very depends on rule base of fuzzy logic. Fuzzy rule base are yielded through the knowledge of the process system [7-9]. In this paper, input signal of fuzzy logic control is current of induction motor and output signal of fuzzy logic control is bearing condition faults of induction motor used in home water pump system such as normal, front fault, rear fault, and both faults.

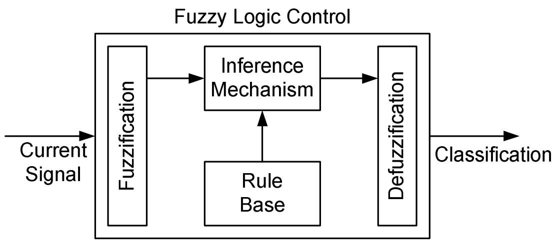

Figure 4. Block diagram of fuzzy logic control

2.4 Taking Data of Induction Motor Current

Taking data of induction motor current is shown in Figure 4. Taking data of induction motor (IM) current is conducted by connecting output current transformer (CT) to audio input of personal computer through probe oscilloscope circuit. Current of IM entered through line in audio of personal computer is read and stored using soundcard oscilloscope software version 1.41.

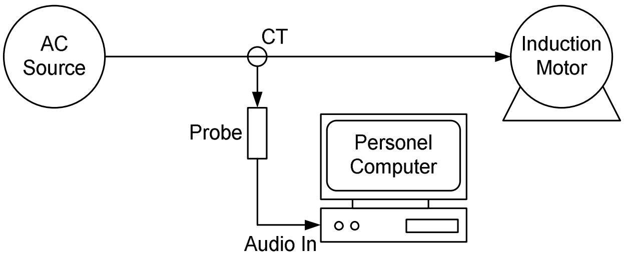

Figure 4. *Taking current data of IM.*

3. RESULT AND ANALISIS

Experimental setup of induction motor (IM) bearing fault classification used in home water pump system using fuzzy logic control is shown Figure 5. Furthermore, results of experiment setup are used to validate the fuzzy logic control model of IM bearing fault classification using SIMULINK-MATLAB. Parameters of IM are nominal voltage of 220 volts, frequency of 50 Hz, nominal power of 125 watts, total heat of 33 meters, suction head of 9 meters, and maximum capacity of 42 liter per minutes.

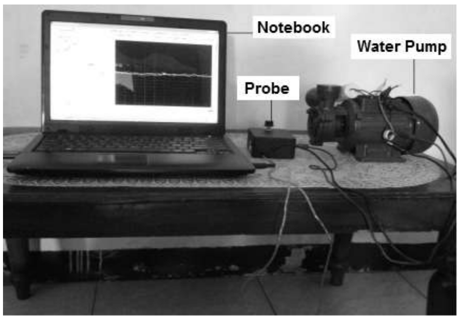

Figure 5. *Experiment setup of IM bearing fault classification*

3.1 Data of Induction Motor (IM) Current

Data of induction motor current is taken using soundcard oscilloscope software version 1.4 for bearing normal (N), front bearing fault (F), rear bearing fault (R), and both bearings fault (B). Figure 6, Figure 7, Figure 8 and Figure 9 show the current waveforms of IM for four bearing fault conditions.

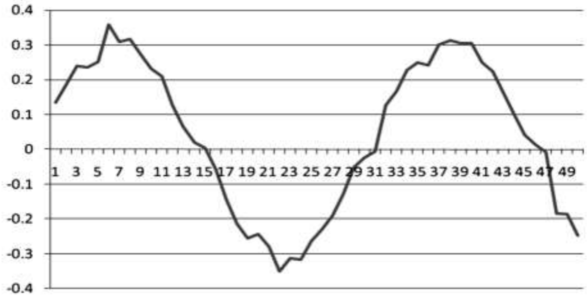

Figure 6. *Current waveform of IM for normal condition*

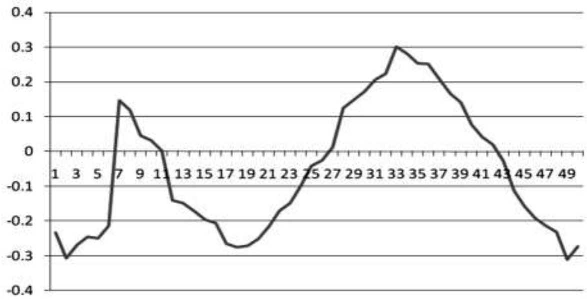

Figure 7. *Current waveform of IM for front bearing fault condition*

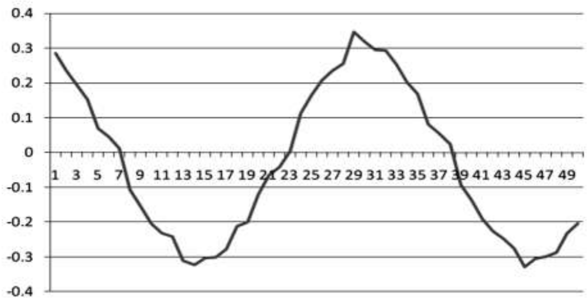

Figure 8. *Current waveform of IM for rear bearing fault condition*

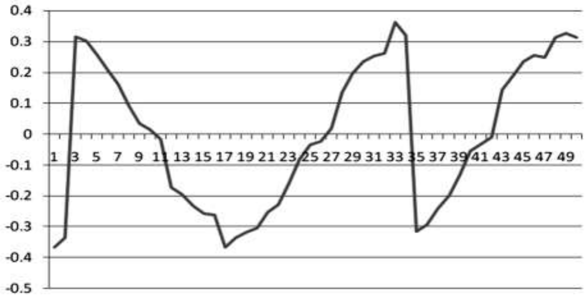

Figure 9. *Current waveform of IM for both bearing fault condition*

3.2 Features Extraction.

Features extraction of IM current waveform for 4 bearing fault conditions are done using Fast Fourier Transform (FFT). Feature extractions are based on Equation (1) and produce the magnitude of the n^{th} component FFT (C_n). Table 1 show the magnitude of the n^{th} component FFT (C_n) for each bearing fault condition.

Table 1. *Magnitude of the n^{th} component FFT (C_n)*

n^{th} component of FFT	Bearing condition			
	Normal (N)	Front fault (F)	Rear fault (R)	Both fault (B)
1	2.9528	0.1879	0.8783	1.8315
2	1.0375	1.9709	1.8326	1.34
3	0.2116	0.9284	0.7423	0.5156
4	0.2178	0.6013	0.633	0.197
5	0.0803	0.6013	0.3421	0.3817
6	0.024	0.3162	0.3545	0.2811
7	0.1609	0.3704	0.3241	0.0764
8	0.0564	0.254	0.308	0.1939
9	0.0564	0.254	0.308	0.1939
10	0.1609	0.3704	0.3241	0.0764

3.3 Classification of Bearing Fault using Fuzzy Logic Control

Fuzzy logic control (FLC) method used in bearing fault classification of IM is FIS SUGENO type. Design of FLC model for bearing fault classification has ten inputs and an output. Ten inputs represent 1^{st} – 10^{th} components of FFT (C_1 – C_{10}) from feature extraction process of induction motor current for each fault conditions. Whereas, an output of FLC is fault conditions of induction motor bearing. FLC model of bearing fault classification can be seen in Figure 10.

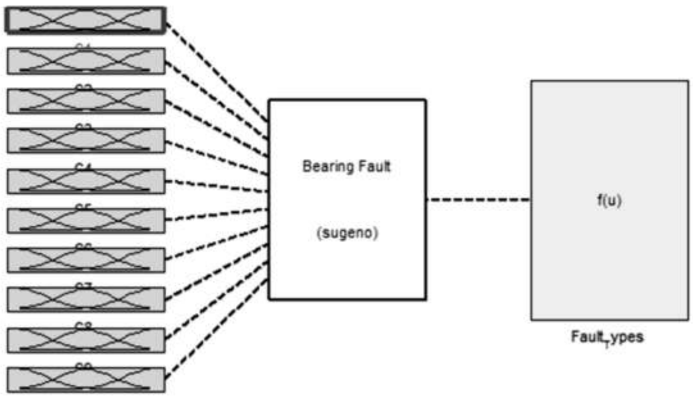

Figure 10. *FLC model for fault classification of induction motor bearing*

Each input of FLC model has 4 membership functions (MF). This membership functions describe 4 bearing fault conditions such as normal (N), front fault (F), rear fault (R), and both faults (B). Parameters of each membership functions base on the n^{th} component of FFT in feature extraction process. Figure 11 show 4 membership functions for first input (C_1).

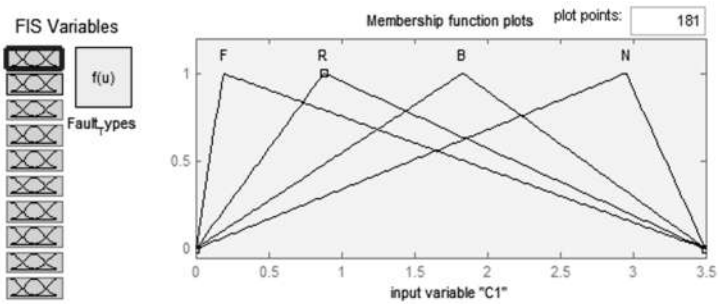

Figure 11. *Membership functions for first input (C_1)*

An output of FLC model also has 4 membership functions. Figure 12 express membership function for an output of FLC model. Whereas, the value of membership functions for a FLC output is shown in Table 2.

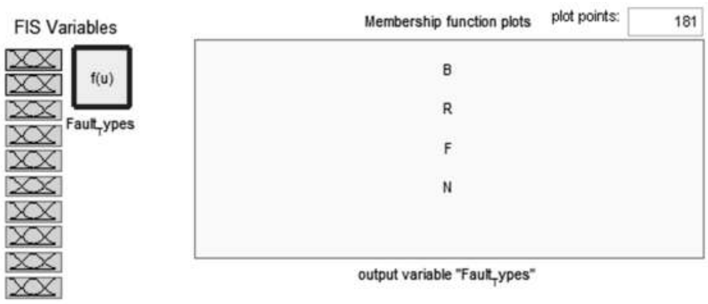

Figure 12. *Membership functions for an output of FLC*

Table 2. Value of membership functions for an output of FLC

Bearing Conditions	Values
Normal (N)	0
Front fault (F)	0.333
Rear fault (R)	0.666
Both fault (B)	1

The proposed FLC model is validated to indicate its performances. Its performances base on error value between design of FLC output and examination value of FLC output. Examination of FLC model is conducted using SIMULINK-MATLAB. Examination of FLC model using SIMULINK-MATLAB can be seen in Figure 13.

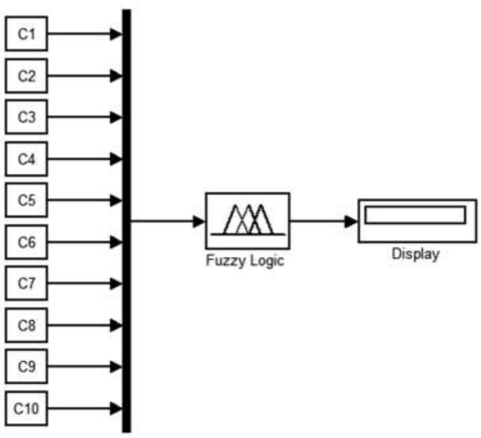

Figure 13. Examination of FLC model using SIMULINK-MATLAB

Examination results of proposed FLC model for each bearing fault condition are shown in Table 3. Examination results of proposed FLC model are compared with value of FLC output according to Table 2.

Examination results show that FLC model for IM bearing fault classification is successfully done, because error values of FLC model are less than 5%.

Table 3. *Result assessments of proposed FLC model*

Bearing Conditions	Values	Assessment
Normal (N)	0	0.047
Front fault (F)	0.333	0.349
Rear fault (R)	0.666	0.641
Both fault (B)	1	0.975

4. CONCLUSION

Fuzzy logic control (FLC) applied in fault classification of induction motor (IM) bearing has been presented and discussed. Fuzzy logic control (FLC) method is used to select and classify fault bearing of IM used in water pump system. The classification of bearing faults consist of four conditions such as normal (N), front bearing fault (F), rear bearing fault (R), and both bearings fault (B). The classification process is divided in three stages such as taking data of IM currents, features extractions, and fault classification using FLC model. The proposed FLC model is clarified to indicate its performances based on error values between design of FLC output and examination value of FLC output. Examination results show that FLC model is successfully conducted to classify the induction motor bearing fault which error values are less than 5%.

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MELANOMA CLASSIFICATION USING AUTOMATIC REGION GROWING FOR IMAGE SEGMENTATION

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ABSTRACT

Melanoma or skin cancer is one of the most common cancer in the world and can be fatal if not diagnosed early. Many methods have been developed to perform the segmentation process of melanoma classification, including region growing. However region growing method has disadvantages, such as there is a threshold parameter that must be set and the seed parameter that must be manually determined by the user. In this research, we proposed a system for melanoma classification that use automatic region growing to perform image segmentation. The analysis of interclass variance of the overall intensity of melanoma image is implemented to obtain the seed point and threshold parameter values that can provide optimal segmentation results for each image automatically. Then several features are extracted from the melanoma object and classification is performed to classify benign and malignant melanoma. The average accuracy, sensitivity, and specificity of the automatic region growing method on 12 test images were 97.6%, 94.8%, and 98.7%, respectively. Based on the experimental results, the automatic region growing method gives better segmentation results than the region growing method because the threshold value used is adaptive in accordance with the grayscale information of the input image and because the proposed method is able to provide several seed points automatically. The classification result of 30 images of benign melanoma and 30 images of malignant melanoma give 83.3%, 80.0%, and 86.7% average value of accuracy, sensitivity, and specificity, respectively.

Keywords: *Automatic Region Growing, Classification, Image Segmentation, Melanoma, Statistical Analysis*

1. INTRODUCTION

Melanoma or skin cancer is a type of cancer that starting from the human skin and can spread to other organs of the body. Melanoma is one of the most common cancer in the world and can be fatal if not diagnosed early. Doctor diagnose whether the melanoma is benign or malignant after performing a biopsy examination. If the diagnosed melanoma is still in the early stages (benign), surgery will usually successfully cure this skin cancer. However, if melanoma is not immediately operated until it reaches a severe stage (malignant), treatments are performed only to slow the spread and reduce the symptoms that occur.

There are several researches conducted to facilitate medical personnel in the melanoma classification using computer assistance. According to [1], general researches on melanoma classification consists of four processes, which are image preprocessing, segmentation, feature extraction, and classification. Many methods have been developed to perform the segmentation process of melanoma classification. Those methods can be classified based on their automatic level (automatic and semi-automatic), the number of parameters used, and the required preprocessing method [2]. Segmentation methods that have been used for melanoma segmentation are including

Fuzzy C-means, center split, multiresolution, split and merge, median cut, adaptive thresholding, gradient vector flow, set level, expectation-maximization (EM) level set, and fuzzy-based split-and-merge. According to some comparisons, median cut, adaptive thresholding, and fuzzy-based split-and-merge methods provide good results in robustness to noise [3] [4].

Region growing is a semi-automated segmentation method that performs segmentation processes starting from one starting point (seed) on a user-selected object region that will then grow and combine the surrounding pixels within a given threshold range onto object class. In the field of medical image processing, this method is commonly used to classify melanoma and blood cell detection because both types of images generally have objects that are clumped and have a color range that does not vary much between pixels. However the semi-automatic region growing method has disadvantages, such as there is a threshold parameter that must be set and the seed parameter that must be manually determined by the user. In fact, due to the type of image that is diverse, to get optimal segmentation results, the value of threshold parameter will be different on each type of image.

In this research, we proposed a system for melanoma classification that use automatic region growing to perform image segmentation. To improve robustness, preprocessing using Gaussian filtering is carried out. Furthermore, the analysis of statistical values, which is interclass variance, of the overall intensity of melanoma image is implemented to obtain the seed point and threshold parameter values that can provide optimal segmentation results using region growing for each image automatically. Classification result of the system whether the melanoma in the analyzed image is benign or malignant can be used as a tool for medical personnel in determining the treatment that would be given to the patient.

2. METHODOLOGY

The methodology of the system is consisted of four main stages, which are preprocessing, segmentation, feature extraction, and classification as shown in Figure 1. The segmentation of melanoma is performed using automatic region growing which consist four process, which are calculation of interclass variance, determination of seed's intensity, automatic selection of seed points and threshold value, and region growing.

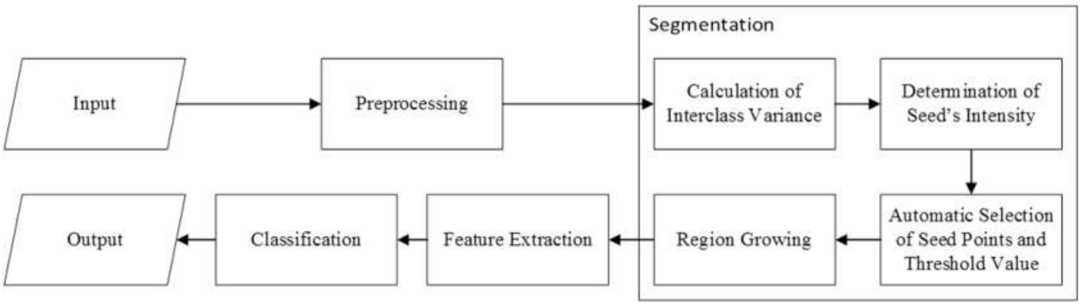
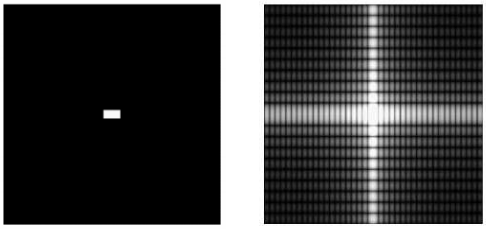


Figure 1. Flowchart of the Proposed System

2.1 Preprocessing

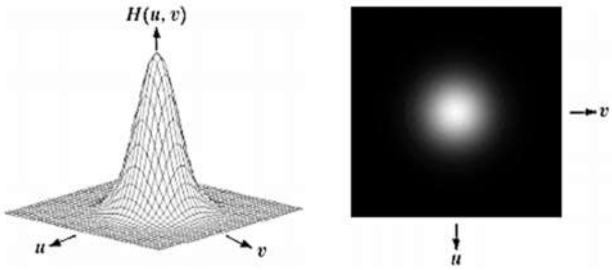
Preprocessing is done to remove unneeded artifacts in the process of detecting melanoma, such as skin hair or air bubbles, thereby increasing the system's robustness to noise. In the preprocessing stage, the color image (RGB) is converted to grayscale. Then Gaussian filtering is performed so that the image becomes smooth and the artifacts such as hair or air bubbles become blur and invisible.

Gaussian filtering use Fourier transform to convert the image from the spatial domain to the frequency domain and then multiply the frequency domain image with the Gaussian low-pass filter for smoothing or blurring. Afterwards, inverse Fourier transform is performed to return the filtered image back to the spatial domain. Figure 2(a) shows an example of the image in the spatial domain and Fig. 2(b) shows the result of the Fourier transformation of Figure 2(a). In the frequency domain as shown in Figure 2(b), the low frequency is collected in the middle of the image, while the high frequency is on the edge of the image.

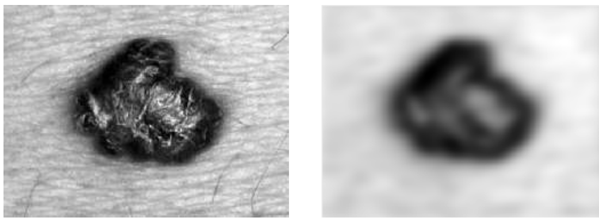


(a) (b)
Figure 2. Image in (a) Spacial Domain and (b) Frequency Domain [5]

Low-pass filter removes high frequency on the image by creating a filter that have one as value for the center of the filter but have zero as value for the edge of the filter. The shape of the Gaussian low-pass filter corresponds to the Gaussian function as shown in Figure 3. If the filter is multiplied by the frequency domain image, only the middle part (low frequency) of the frequency domain image is left. When the filtered image is inversed to spatial domain, it will gives smoothing blurring effect, as shown in Figure 4.



(a) (b)
Figure 3. (a) Plot and (b) Image of Gaussian low-pass filter [5]



(a) *(b)*
Figure 4. Melanoma Image (a) Before and (b) After Preprocessing

2.2 Segmentation

Segmentation method proposed in this research is automatic region growing using interclass variance analysis. Interclass variance analysis is used to determine the seed point and threshold value automatically. First, intensity histogram from the image from preprocessing result *I* is created. The histogram has 256 graylevel intensities.

Afterwards, using each graylevel *t* as a threshold in turn, the interclass variance is calculated between the class on the left and right of the threshold. Interclass variance $\sigma_\omega^2(t)$ is defined as the sum of object class's variance and background class's variance using Equation 1 [6]. Weight ω_i is the cumulative probability that graylevels in class *i* are appear in the image and σ_i^2 is the variance of class *i* where *i*=1 for background and *i*=2 for object.

$$\sigma_\omega^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \quad (1)$$

To determine the graylevel intensity of the region growing's seeds, first the graylevel with the smallest interclass variance *g* is obtained, as written in Equation 2. Then the lowest graylevel found in the image *h* is also obtained, as written in Equation 3. The graylevel intensity of the seed *s* is the mean value between the graylevel with smallest interclass variance and the lowest graylevel found in the image, as written in Equation 4. The lowest graylevel found in the image is used because the melanoma object in the image tends to be darker than the background.

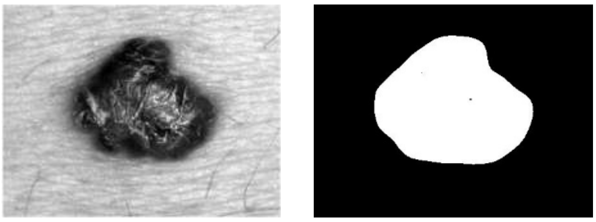
$$g = \arg \min_{0 \le t \le 256} \sigma_{\omega}^{2}(t) \tag{2}$$

$$h = \min_{t \in I} t \tag{3}$$

$$s = \frac{1}{2}(g + h) \tag{4}$$

The seed points for the region growing is the pixels in the image that have a graylevel intensities around the value of s. The threshold value for the region growing is the difference between the graylevel intensity of seed s with the graylevel with smallest interclass variance g. After the seed points and threshold value are obtained, a growing region is performed at each seed points.

Using the seed points as the initialization of the object region, the region growing method adds neighboring pixels of the object region that meets certain criteria into the object region. The criterion is that the pixel must have an intensity whose value is less than or equal to the intensity of the seed s that added or subtracted by the threshold value. The size of the object region continues to widen until no more neighboring pixels meet the criteria. Pixels that are not included in the object region are grouped in the background region. Pixels in the object region will have white color while the pixels in the background region will have black color. Because the proposed automatic region growing method may use more than one seed points, the final result of the segmentation process is the union of the results of region growing of each seed points. Figure 5 shows the example of segmentation process on the melanoma image using automatic region growing. In Figure 5(a), the seed points are marked as red dots.



(a) (b)

Figure 5. (a) Result of Automatic Seed Selection and (b) Result of Segmentation Process

2.3 Feature Extraction

The difference between benign and malignant melanoma can be seen from its size, shape, and color. Benign melanoma has a relatively narrow size, regular shape, and its color tends to be light. Malignant melanoma has a large size and irregular shape because spread of the cancer cells, as well as its color that tends to be dark. Based on that information, the extraction of features that represent the size, shape, and color criteria of the melanoma is performed on the image from segmentation process.

For the size criteria, area ratio of melanoma objects is taken. Because the size of each melanoma image varies, the area ratio of the extent of the melanoma object is the area of the melanoma object divided by the size of the image. The larger the value of area ratio, the larger the size of melanoma. For shape criteria, circumference ratio of the melanoma object is taken. The circumference ratio of the melanoma object is the circumference of the melanoma object divided by the area of the melanoma object. The larger the value of circumference ratio, the more irregular the shape of the melanoma because the regularly shaped objects tend to have a smaller circumference than the irregularly shaped objects.

For color criteria, average of RGB (red, green, blue) color values of the melanoma object (not from the entire image) is taken. To get color feature of the melanoma object, the output image of segmentation process and the input image are used. On the output image of segmentation process, the position of each pixels that have white color (object) is taken. Then the color value information at each position is obtained from the input image and the mean for each red, green, and blue channel is calculated. In total there are five features that are extracted to classify melanoma.

2.4 Classification

Using features obtained from the previous process, classification using the Support Vector Machine (SVM) method is performed to classify the data into two class: benign and malignant. SVM seeks to find the best separator function (hyperplane) to separate vectors from two classes. The best hyperplane is the hyperplane that gives the highest margin value, where margin is the distance between the hyperplane with the vector closest to the hyperplane (support vector). Finding the best hyperplane is equivalent to maximizing margins or spacing between two sets of objects from different classes.

3. EXPERIMENTAL RESULTS

The data used in this research are obtained from the https://isic-archive.com/ repository which is divided into 2 types of classes, namely benign and malignant melanoma, where each class consists of 30 pieces of image as shown in Figure 6 and Figure 7. In addition, from the data, 6 images from each class are selected to be used in the evaluation of segmentation method hence its segmentation's ground truth are created as shown in Figure 8 and Figure 9.

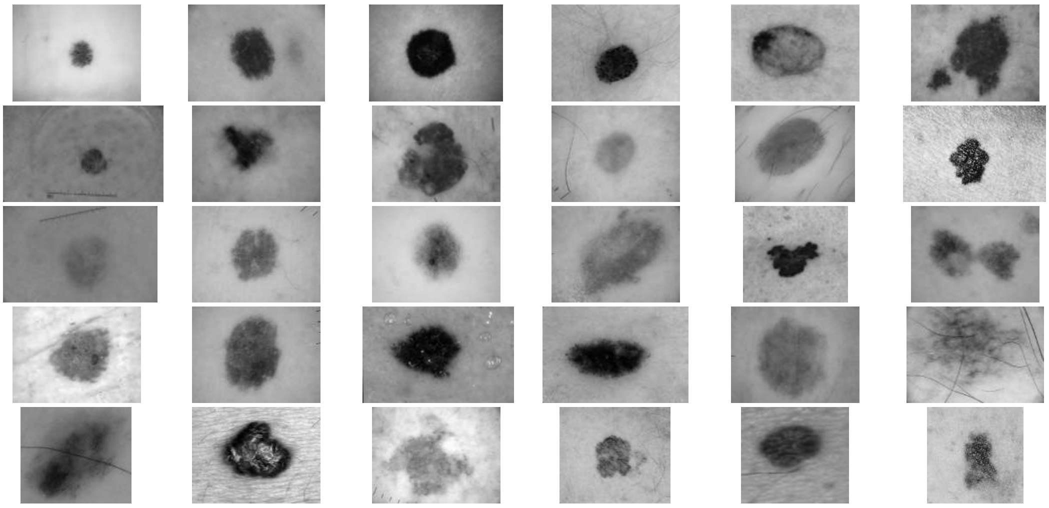


Figure 6. Data of Benign Melanoma

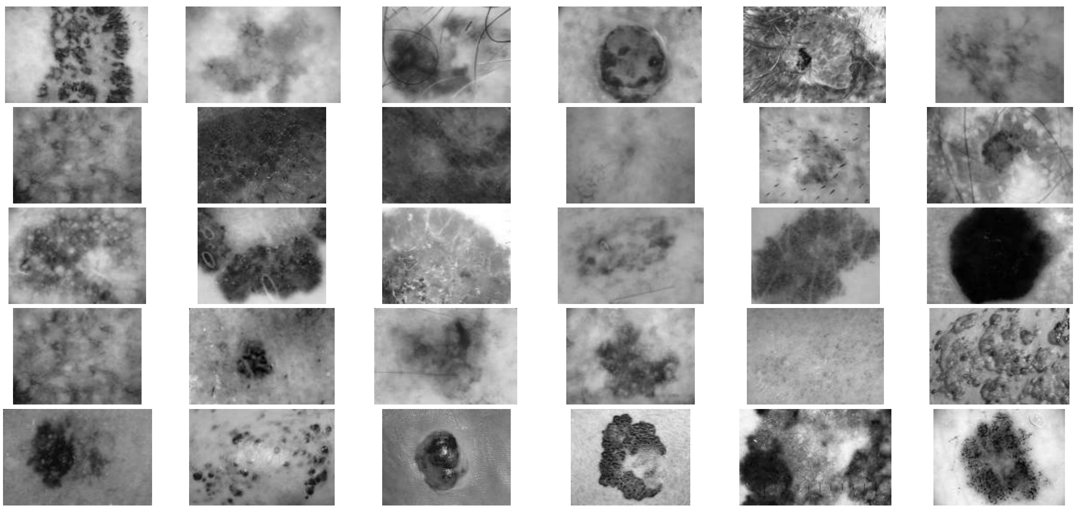
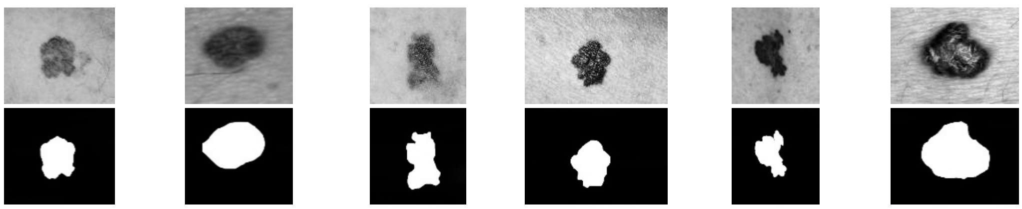
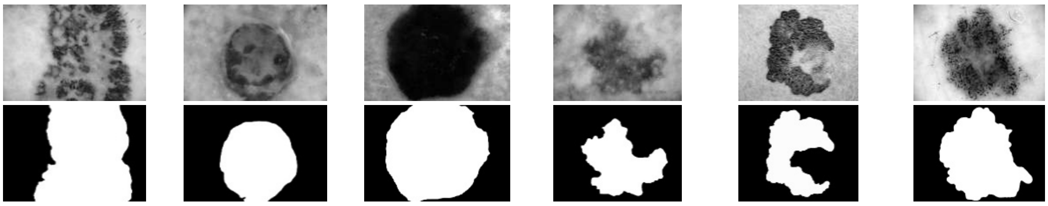


Figure 7. Data of Malignant Melanoma



(1) (2) (3) (4) (5) (6)

Figure 8. Segmentation's Ground Truth of Benign Melanoma



(7) (8) (9) (10) (11) (12)

Figure 9. Segmentation's Ground Truth of Malignant Melanoma

Two experiments were conducted, which are experiment to measure the performance of segmentation methods and experiment to measure the performance of the melanoma classification system. Both in experiment on segmentation methods or classification process, the performance is measured using accuracy, sensitivity, and specificity values that are calculated based on confusion matrix. The confusion matrix is shown in Figure 11, where TP=True Positive, FN=False Negative, FP=False Positive, and TN=True Negative.

		System Output	
		1	**0**
Ground Truth	**1**	TP	FN
	0	FP	TN

Figure 10. Confusion Matrix

Accuracy is the number of data classified correctly. Sensitivity or true positive rate is the number of data in class 1 are classified in class 1. Sensitivity or a true negative rate is the number of data in class 0 are classified in class 0. The formula for calculating accuracy, sensitivity, and specificity is consecutively written in Equation 5-7. In the experiment on segmentation method, class 1 is the object area and class 0 is the background area. In the experiment on classification process, class 1 is the malignant melanoma and class 0 is the benign melanoma.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (5)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (6)$$

$$Specificity = \frac{TN}{FP+TN} \quad (7)$$

3.1 Experiment on Segmentation Method

Experiment were conducted on 12 images in Figure 8 an Figure 9 to compare the performance of the proposed automatic region growing method with the (original) region growing method. For the region growing method, the seeds used in the first seed value are obtained using the automatic region growing method and the threshold value used is 0.18, which is obtained from the average threshold value in the automatic region growing method on 12 image. Figure 11 shows the segmentation results of the automatic region growing. Figure 12 shows the segmentation results of the region growing method. Performance comparison between automatic region growing and region growing method is shown in Table 1. From Table 1 it appears that the automatic region growing method gives more accurate segmentation results than the (original) region growing method.

(1) (2) (3) (4) (5) (6)

Figure 11. Segmentation Results Using Automatic Region Growing

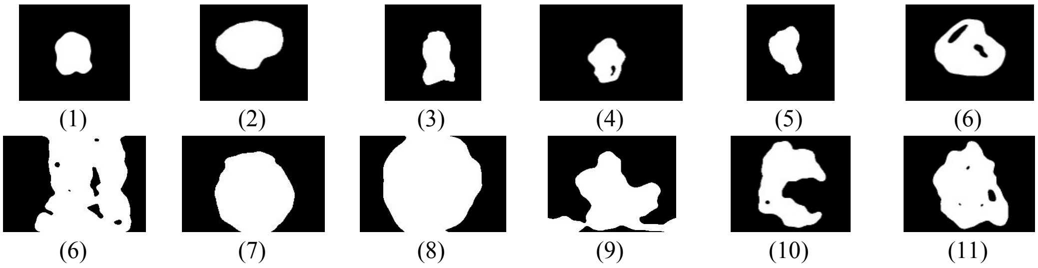


Figure 12. Segmentation Results Using Region Growing (Original)

Table 1. Experiment Result on Segmentation Method

No	Automatic Region Growing			Region Growing		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
1	**99.0**	96.8	**99.3**	98.6	**99.7**	98.5
2	**97.8**	92.9	**99.1**	96.2	**96.6**	96.2
3	98.3	91.3	**99.5**	98.3	**92.3**	99.4
4	**99.2**	**91.5**	99.9	98.8	86.9	**100.0**
5	97.8	100.0	97.5	97.8	100.0	97.5
6	**97.4**	**99.6**	96.7	96.6	90.8	**98.3**
7	**98.5**	**98.2**	98.9	95.5	92.5	**99.4**
8	**97.0**	95.8	**97.6**	96.5	**97.1**	96.2
9	97.1	96.0	**98.5**	**97.2**	**96.2**	98.4
10	**95.9**	90.7	**98.2**	88.9	**96.0**	85.9
11	**98.7**	**99.0**	98.6	98.6	97.7	**99.0**
12	**94.0**	**86.1**	100.0	91.1	79.2	100.0
Average	**97.6**	**94.8**	**98.7**	96.2	93.8	97.4

3.2 Experiment on Classification Process

For classification process, the experiment was conducted using *k*-fold cross validation method with *k*=10. The *k*-fold cross validation method is used to validate the accuracy of a system. In the *k*-fold cross validation method, the input data will be divided into *k* folds in which each fold has the same amount of data and has an even distribution of classes. Then the accuracy of the system is calculated using one fold as testing data and the rest folds as training data. Fold is chosen as testing data alternately until all folds has become testing data. Accuracy of the system is calculated from the average accuracy of each fold of testing data. Table 2 shows the performance of the classification system using 10-fold cross validation. The accuracy score is only about 80% because there are some malignant melanoma images that look similar with benign melanoma.

Table 2. Experiment Result on Classification Process

Fold	Accuracy(%)	Sensitivity (%)	Specificity (%)
1	66.7	66.7	66.7
2	100.0	100.0	100.0
3	83.3	66.7	100.0
4	83.3	66.7	100.0
5	83.3	100.0	66.7
6	83.3	100.0	66.7
7	83.3	66.7	100.0
8	66.7	33.3	100.0
9	83.3	100.0	66.7
10	100.0	100.0	100.0
Average	**83.3**	**80.0**	**86.7**

4. CONCLUSION

Proposed system for melanoma classification that use automatic region growing to perform image segmentation can provide threshold value and seed points for region growing automatically. The system is consisted of four main stages, which are preprocessing, segmentation, feature extraction, and classification. Preprocessing is used to remove unnecessary artifacts thereby increasing robustness to noise. Segmentation process using the proposed automatic region growing is performed. The extracted features are the area ratio, the circumference ratio, and the color of the melanoma object. Classification of benign or malignant melanoma was performed using Support Vector Machine (SVM).

The average accuracy, sensitivity, and specificity of the automatic region growing method on 12 test images were 97.6%, 94.8%, and 98.7%, respectively. Based on the experimental results, the automatic region growing method gives better segmentation results than the region growing method because the threshold value used is adaptive in accordance with the grayscale information of the input image and because the proposed method is able to provide several seed points automatically. The classification result of 30 images of benign melanoma and 30 images of malignant melanoma using 10-fold cross validation method give 83.3%, 80.0%, and 86.7% average value of accuracy, sensitivity, and specificity, respectively. This is because there are some images of malignant melanoma that look similar with benign melanoma.

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