Brain Disease Classification using Different Wavelet Analysis for Support Vector Machine (SVM)

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Abstract: The brain is one of the vital organs, some diseases attack the brains aregliomas and brain cancer. Glioma is a type of tumor in the human brain, while brain cancer is a condition of abnormal cell growth in the brain. The danger of these two diseases often causes death. Both diseases have different treatment methods. Therefore, it is necessary to classify MRI images accurately. Extraction of features in images can affect the classification process. In this study, we compare the best feature extraction methods that can be used in brain MRI, wavelet decomposition and wavelet texture analysis. In this study, to test the accuracy of the two methods is using an SV Mas classification method. The results show the wavelet texture analysis had better results than using wavelet decomposition. This statement is indicated by the results of accuracy using wavelet texture analysis of 82.14% compared to the accuracy of using wavelet decomposition of 75%.

1 INTRODUCTION

The brain is the center of the human nerves, therefore the brain becomes one of the most important organs for humans. If the brain has a disease, then it will be very dangerous and often lead to death. Some diseases that often attack the brain such as glioma and brain cancer. Cancer appears from the growth of abnormal cells in a part of the body. If abnormal cell growth is not treated immediately, cancer cells will attack the surrounding tissues (Jong 2005). Whereas glioma is one type of brain tumor that most often attack humans. Approximately 13,000 cases of death each year are due to glioma in the brain (de Rooij et al. 2016). Most people with new brain disease realize it after entering an advanced stage. Treatment of brain cancer and glioma is very different; therefore, the right classification is needed to take the most correct action.

Using an increasingly advanced technological development, classification and diagnosis of brain diseases can be performed using numerical calculations. Numerical calculations are performed by taking an existing MRI image value. Previous research has performed accuracy testing in the use of MRI images taken from prostate cancer photography (Pokorny et al. 2014). Through an existing MRI image, you can take the feature to be detected. Feature extraction of MRI images can be performed using several different methods. in previous research, feature extraction using wavelets for iris image matching(Birgale and Kokare 2009). Wavelets are often used to perform feature extraction because wavelets are a process that can feature extraction without removing the essential elements present in an image.

Previous research of wavelet results was used to perform feature extraction on mammogram data(Ferreira and Borges 2003). The two studies took the wavelet results in the wavelet decomposition image as a feature extraction process. In another research, the wavelet is used as a texture analysis of an image to perform a breast tumor diagnosis(Chen et al. 2002). Texture analysis using wavelets is also used to perform knee osteoarthritis detection(Riad et al. 2018). From some of these studies, identification of images using wavelet decomposition or texture analysis using wavelets. Both uses of the wavelet have results for classification of the tested image.

Previous studies of classification were performed using the Support Vector Machine (SVM) as a method of identifying the type of cancer(Wang and Cai 2018). Classification using the Support Vector

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Machine (SVM) is also used to classify breast cancer(Lo and Wang 2012). From several previous studies, classification of images of brain disease can use Support Vector Machine (SVM).

Looking at some of the existing research and problems, this study aims to determine the best feature extraction method for brain disease classification using the Support Vector Machine (SVM) as a method of classifying. In this research, the feature extraction method to be compared is the decomposition of the wavelet transform with wavelet analysis transformation. The results of this study are expected to determine the best feature extraction method.

2 LITERATURE REVIEW

2.1 Brain Disease

Brain disease is a disorder or abnormality that occurs in the brain. Abnormalities that occur can be an increase in the volume of brain that is not accompanied by skull bone growth, an unfair the growth of cells in the brain, etc. People affected by brain disease, generally experiencing sleep disorders. in previous research states that people aged about 65 years take a risk for brain diseases than people under age(Nadesul 2011). Some diseases that attack the brain include brain cancer, glioma, or Alzheimer's.

2.2 Magnetic Resonance Imaging (MRI)

Magnetic resonance imaging (MRI) is one of the shooting techniques that uses magnetic resonance of a hydrogen atom. The magnetic field used for shooting magnitude between 0.064 to 1.5 Tesla(Marinus T. Vlaardingerbroek 2013).

2.3 Median Filter

The Median Filter is a method used to remove pixels that remove noise in the image. Noise is a pixel in the image that can interfere in the process of identifying images. Using the median filter, the resulting image will leave the image actually detected, uninterrupted by the noise in the image(Shih 2010).

2.4 Adaptive Histogram Equalization (AHE)

Adaptive histogram equalization is one method used to make improvements pixels by correcting the point on the image. Improvements made by leveling the spread of intensity values in an image(S Jayaraman, S Esakkirajan 2009). Through the AHE process, it can improve contrast and clarify an image. to calculate and do AHE is used Equation 1, and Equation 2.

$$T(r_k) = \sum_{j=0}^{k} p_r(r_j) \tag{1}$$

$$p(r_k) = {}^{n_k}/_{n} \tag{2}$$

r_k =Gray level in the picture
n_k =Number of pixels in r_k
$p(r_k)$ =Normalization of the image histogram
$T(r_k)$ =Renewal of pixel values

2.5 Structuring Element (SE)

Structuring Element (SE) is a pixel arrangement in the drawing, with the center setting being in the center of the structure of the created element. The arrangement of elements is usually performed to perform morphological operations on the image. the arrangement of elements in the image can be used in dilation or erosion processes. Dilation process is a process of adding pixels to an already formed area with elemental structures, whereas erosion is the opposite of a dilation process(Shih 2010). The dilation and erosion process can be performed using Equation 3 and Equation 4 respectively.

$$g(x,y) = f(x,y) \oplus SE \tag{3}$$

$$g(x,y) = f(x,y) \ominus SE \tag{4}$$

The morphological operation process can combine the erosion process then continued with the dilation process which can be called by opening process. The opening process can be expressed by using the functional composition of Equation 3 and Equation 4, so obtained as in the following Equation 5.

$$f(x,y) \circ SE = (f(x,y) \ominus SE) \oplus SE \tag{5}$$

2.6 Discrete Wavelet Transform(DWT)

Discrete Wavelet Transform (DWT) is a method often used to reduce a picture. The level of reduction performed depends on the energy contained and the transformation performed. Through the wavelet, the image transformation will be identified between the intense or not. The results of the identification will get the reduced image without losing the visual quality of the image (Breckon 2011).

DWT process, the image will be divided into two: High-pass initialized with g [n], and low-pass is initialized with h [n]. In image data, DWT will reduce twice, DWT to row, and will be continued with DWT to the column. Since the DWT process happens twice, the image will be generated from one DWT level of 4 sub-bands. The four sub-bands include Low-Low (LL) which has lower resolution, Low-High (Vertical), High-Low (Horizontal), High-High (Diagonal)(Seymour 1999). The process of forming four sub-bands will be illustrated in Figure 1.

Decomposition of Discrete Wavelet Transform (DWT) is written in Equation 6.

$$c(j,k) = \sum_{t} f(t)\psi_{j,k}(t) \qquad (6)$$

With$\psi_{j,k}$is the mother wavelet formulated by Equation 7.

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-k2^j}{2^j}\right) \qquad (7)$$

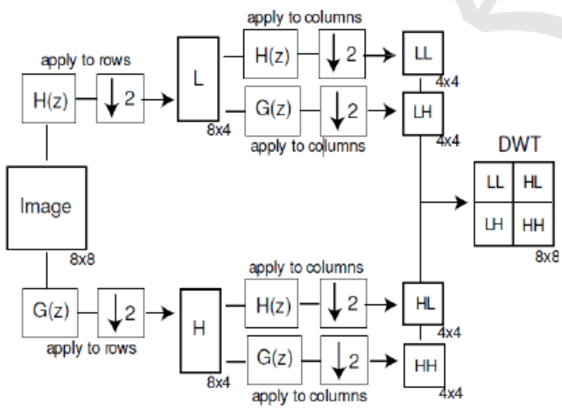
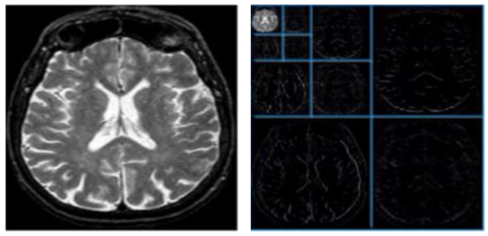


Figure 1: Wavelet decomposition process

Each sub-band produced from the DWT process yields a detailed coefficient (LH, HL, HH), approximation coefficient (LL), which is formulated by Equation 8.

$$W_{\psi}[j,k] = \frac{1}{\sqrt{N}}\sum_{m=0}^{N-1} x[m]\psi_{j,k}[m] \qquad (8)$$

With the resulting wavelet results as in Figure 2.(El-dahshan et al. 2014)



(a) (b)

Figure 2 : (a) wavelet level 1, (b) wavelet level 3

From the results obtained, feature retrieval uses wavelet texture analysis by taking energy, average and standard deviation of the wavelet image. To take these three values we can use Equations 9, 10, 11.

$$E = \frac{1}{M^2XN^2}\sum_{i=1}^{M}\sum_{j=1}^{N}|x_{i,j}|^2 \qquad (9)$$

$$\mu = \frac{1}{M\ X\ N}\sum_{i=1}^{M}\sum_{j=1}^{N}|X_{i,j}| \qquad (10)$$

$$S = \sqrt{\frac{1}{M\ X\ N}\sum_{i=1}^{M}\sum_{j=1}^{N}(X_{i,j}-\mu)^2} \qquad (11)$$

2.7 Support Vector Machine (SVM)

Support Vector Machine is one of the methods used to perform data classification. Classification performed by SVM, and by dividing the regional area from a set of existing data. Sharing and grouping data using the Support Vector Machine (SVM) by forming a hyperplane. In order to facilitate the establishment of a hyperplane, a kernel is required. Using kernel function the data will be brought to a higher dimension. In this research kernel function used is the Gaussian function. The result using a kernel will make it easier to form a hyperplane(Jiawei Han and Micheline Kamber 2006).

2.8 Recognition Rate

Recognition Rate is one method that can be used to calculate the accuracy value or truth value of the calculation of the classification results(Jiawei Han and Micheline Kamber 2006). In the recognition rate method, the accuracy value can be calculated through Equation 12.P is the total predicted correctly and N is the total of data.

$$Accuracy = \frac{P}{N} \times 100\%. \quad (12)$$

3 METHODS

This study, to test the accuracy of the two wavelet methods, was carried out in several stages. The first stage is preprocessing, followed by feature extraction using the wavelet analysis method, and the Support Vector Machine (SVM) method is used to classify it. then to test the level of accuracy of different wavelet analyzes using the Recognition Rate method. to describe the net of the process in this study will be illustrated in Figure 3.This Research uses data in the form of MRI images of the brain. MRI images of the brain used amounted to seventy images with 42 images classified Alzheimer's, 8 glioma clarified images, 8 classified images of cancer, and twelve pictures classified normal brain images. From some of the available data, classification testing can use various kinds of data sharing tests with training data.

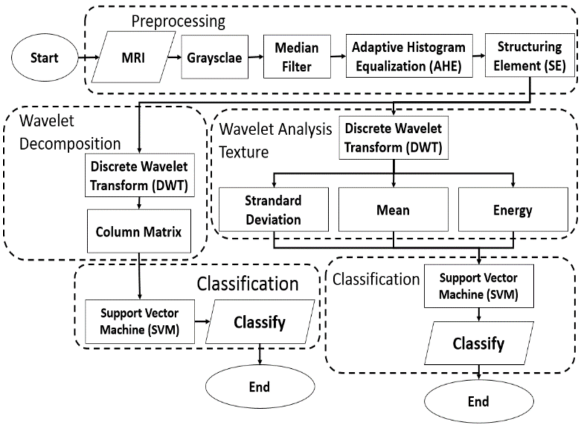


Figure 3: Brain Disease Classification Design System

Before the processing of existing MRI images, the data repaired using preprocessing. The first step in preprocessing is to convert an MRI image into a grayscale image. This process is used to determine the difference of pixel intensity in the picture. knowing the difference in intensity they have, it is hoped that it can be easy to find and distinguish between brain features and brain disease.

After getting a grayscale image, the values on the image clarified and leveled using Adaptive Histogram Equalization (AHE). The processed image will be clarified using Equation(1). The result of this process the image used will produce a clearer image, no more the difference in intensity value which is very far from the average pixel value.

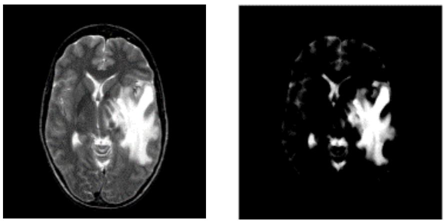
The next image will be performed by the morphological opening operation. The opening process used the erosion process followed by the dilation process.in this process, the image is processed using Equation (5). Through the opening process, unimportant features are automatically deleted.

The resulting image of preprocessing, then performed feature extraction using wavelet decomposition. The result of the opening process will be feature extraction using Equation six as the mother wavelet performed and using Equation six as the wavelet decomposition process. Next, the image is broken down into four different sub-bands using eight. In addition to using wavelet decomposition, feature extraction is performed using wavelet texture analysis. Energy, average, and standard deviation used for feature extraction in wavelet texture analysis

From the decomposition process and texture, analysis can be continued with the classification process. Classification of brain disease images performed using one of the Support Vector Machine (SVM) methods. Using the Support Vector Machine (SVM) the image will be classified into 3 classes, i.e. normal brain images, brain images affected by cancer, and images of the brain affected by glioma. In the classification process using Support Vector Machine (SVM) data will be divided into training data and test data. Data sharing for training and testing conducted three times, with 60% training, 40% testing; 75% training, 25% testing; 70% training, 30% testing. The result of the three experiments will be known for optimal feature extraction for classification testing.

4 RESULTS AND DISCUSSION

The classification of disease images was performed using wavelet feature extraction and classification using the SVM method. Before feature extraction, the image is repaired using preprocessing.in the preprocessing phase the image is repaired using several methods. improvements made at the preprocessing stage include the conversion of MRI images to grayscale, removal of pixel noise in the image, improved contrast, and the formation of elements using structural elements. The results of preprocessing are shown in Figure 4.



(a) (b)

Figure 4:(a) Cancer Brain Image, (b) Preprocessing Result Cancer Brain Image

After the preprocessing stage, images are processed using two different feature extractions. The first method is wavelet decomposition. In wavelet decomposition. in the wavelet decomposition process, the mother wavelet used is 'Haar'the results of the wavelet decomposition process are divided into 4 sub-bands namely vertical decomposition, horizontal decomposition, diagonal decomposition, and approximation. but in this study, the Sub-band used was Low-Low or Approximation. The results of wavelet decomposition are shown in Figure 5

(a) (b)

Figure 5: (a) Wavelet Decomposition Level 3, (b) Approximation Wavelet Level 3

The second method is to use wavelet analysis texture. Analysis texture used by taking some values from the wavelet image. The values taken are mean, standard deviation, and energy. These three values represent for each image generated on the wavelet process. The results of wavelet analysis texture using level 3 are presented in Table 1.

The results of wavelet decomposition and analysis texture will then be classified using SVM. Each wavelet decomposition and wavelet analysis texture are processed separately. After the classification of the two different feature extractions, resulting in accuracy presented in Table 2.

Table 1: Results of Texture Analysis in Approximation Level 3.

Feature	Sub-band	Level	Data				
			1	2	.	41	42
Mean	HL	1	18,57	11,472		13,257	21,363
	LH		18,57	11,472		13,257	21,363
	HH		18,57	11,472		13,257	21,363
	HL	2	37,139	22,945		26,515	42,727
	LH		37,139	22,945		26,515	42,727
	HH		37,139	22,945		26,515	42,727
	HL	3	74,279	45,89		53,03	85,454
	LH		74,279	45,89		53,03	85,454
	HH		74,279	45,89		53,03	85,454
	LL		74,279	45,89		53,03	85,454
Standart Deviation	HL	1	42,673	27,921		46,538	49,971
	LH		42,673	27,921		46,538	49,971
	HH		42,673	27,921		46,538	49,971
	HL	2	79,488	51,411		90,395	94,088
	LH		79,488	51,411		90,395	94,088
	HH		79,488	51,411		90,395	94,088
	HL	3	133,65	82,114		170,79	166,20
	LH		133,65	82,114		170,79	166,20
	HH		133,65	82,114		170,79	166,20
	LL		133,65	82,114		170,79	166,20
Energy	HL	1	12,166	12,807		11,147	11,779
	LH		12,166	12,807		11,15	11,779
	HH		12,166	12,807		11,15	11,779
	HL	2	10,63	10,827		10,3	10,473
	LH		10,63	10,827		10,3	10,473
	HH		10,63	10,827		10,3	10,473
	HL	3	7,903	7,275		8,91	8,311
	LH		7,903	7,275		8,91	8,311
	HH		7,903	7,275		8,91	8,311
	LL		7,903	7,275		8,914	8,311

Table 2: Results of Accuracy from Wavelet Decomposition and Wavelet Analysis of Texture.

Data distribution		Level	Accuracy	
Training	Testing		Decomp	Analysis

			osition	Texture
60%	40%	2	75%	78.57%
		3	75%	82.14%
		4	75%	75%
70%	30%	2	66.67%	71.43%
		3	66.67%	66.67%
		4	66.67%	66.67%
75%	25%	2	61.11%	72.22%
		3	61.11%	72.22%
		4	61.11%	61.11%

The results in Table 2 show the wavelet analysis texture has the highest accuracy of 82.14%, while wavelet decomposition has the highest accuracy with 75% value. From the results show that the analysis texture has better accuracy when compared with the accuracy value generated by wavelet decomposition. The highest accuracy of Analysis Texture is shown when using wavelet level 3, with 60% data distribution as training data, and 40% data testing.

5 CONCLUSIONS

The results show that wavelet texture analysis is better than wavelet decomposition as feature extraction method. The statement was supported by the best accuracy results obtained wavelet texture analysis of 82.14%, while the best accuracy possessed by the wavelet decomposition method was 75%. Seeing some of these statements, it can be concluded that the best feature extraction method using the brain image is wavelet analysis texture method.

REFERENCES

Birgale, L V, and M Kokare. 2009. "Iris Recognition Using Discrete Wavelet Transform." *Digital Image Processing, 2009 International Conference on* (April): 147–51.

Breckon, C. Solomon; T. 2011. "Fundamentals of Digital Image Processing : A Practical Approach with Examples in Matlab. John Wiley & Sons, Inc., 2011." *John Wiley & Sons Inc*.

Chen, Dar-Ren et al. 2002. "Diagnosis of Breast Tumors with Sonographic Texture Analysis Using Wavelet Transform and Neural Networks." *Ultrasound in Medicine & Biology* 28(10): 1301–10. http://www.sciencedirect.com/science/article/pii/S0301562902006208.

El-dahshan, El-sayed A, Heba M Mohsen, Kenneth Revett, and Abdel-badeeh M Salem. 2014. "Computer-Aided Diagnosis of Human Brain Tumor through MRI : A Survey and a New Algorithm." *Expert Systems with Applications* 41(11): 5526–45. http://dx.doi.org/10.1016/j.eswa.2014.01.021.

Ferreira, Cristiane Bastos Rocha, and Díbio Leandro Borges. 2003. "Analysis of Mammogram Classification Using a Wavelet Transform Decomposition." *Pattern Recognition Letters* 24(7): 973–82.

Jiawei Han and Micheline Kamber. 2006. *Data Mining*. Second. San Francisco: Morgan Kaufmann Publisher.

Jong, Wim de. 2005. "Kanker, Apakah Itu? Pengobatan, Harpaan Hidup, Dan Dukungan Keluarga."

Lo, Chien Shun, and Chuin Mu Wang. 2012. "Support Vector Machine for Breast MR Image Classification." *Computers and Mathematics with Applications* 64(5): 1153–62. http://dx.doi.org/10.1016/j.camwa.2012.03.033.

Marinus T. Vlaardingerbroek, Jasques A. Boer. 2013. *Magnetic Resonance Imaging Theory and Practice.Pdf*. New York: Springer Science & Business Media.

Nadesul, Handrawan. 2011. *Menyayangi Otak.Pdf*. Jakarta: Buku Kompas.

Pokorny, Morgan R. et al. 2014. "Prospective Study of Diagnostic Accuracy Comparing Prostate Cancer Detection by Transrectal Ultrasound-Guided Biopsy versus Magnetic Resonance (MR) Imaging with Subsequent Mr-Guided Biopsy in Men without Previous Prostate Biopsies." *European Urology* 66(1): 22–29.

Riad, Rabia et al. 2018. "Texture Analysis Using Complex Wavelet Decomposition for Knee Osteoarthritis Detection: Data from the Osteoarthritis Initiative." *Computers and Electrical Engineering* 68(October 2017): 181–91.

de Rooij, Maarten et al. 2016. "Accuracy of Magnetic Resonance Imaging for Local Staging of Prostate Cancer: A Diagnostic Meta-Analysis." *European Urology* 70(2): 233–45. http://dx.doi.org/10.1016/j.eururo.2015.07.029.

S Jayaraman, S Esakkirajan, T Veerakumar. 2009. *Digital Image Processing.Pdf*. New Delhi: Tata McGraw Hill Education Private Limited.

Seymour, Lynne. 1999. "Image Processing and Data Analysis, The Multiscale Approach." 94(448): 1389.

Shih, Fy. 2010. "Image Processing and Mathematical Morphology: Fundamentals and Applications."

Wang, Shao Peng, and Yu Dong Cai. 2018. "Identification of the Functional Alteration Signatures across Different Cancer Types with Support Vector Machine and Feature Analysis." *Biochimica et Biophysica Acta - Molecular Basis of Disease* 1864(6): 2218–27. http://dx.doi.org/10.1016/j.bbadis.2017.12.026.