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Support vector machine based discrete wavelet transform for magnetic resonance imaging brain tumor classification

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ABSTRACT

Here, a brain tumor classification method using the support vector machine (SVM) algorithm by utilizing discrete wavelet transform (DWT) transformation and feature extraction of gray-level co-occurrence matrix (GLCM) and local binary pattern (LBP) has been implemented using the magnetic resonance imaging (MRI) image belong to the low-grade glioma (LGG) or high-grade glioma (HGG) group. SVM algorithm used as a classification method has been widely used in research that raises the topic of classification. Through the formation of a hyperplane between 2 data classes, the SVM algorithm can be said to be a reliable method but does not require complicated computations. The DWT transformation is intended to provide clearer feature details from the MRI image, so that when the feature extraction algorithm is applied, it is expected that the extracted features will differ between benign tumor MRI images and malignant tumor MRI images. In 1 level DWT using high-low (HL) sub-band yield the highest specificity, sensitivity, and accuracy than using 3 levels using HL or low-high (LH) sub-band in LGG MRI image. Compared with another research, our proposed method is slightly better in terms of accuracy to classify the brain tumor image with achieved the accuracy of 98.6486%.

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1. INTRODUCTION

Brain tumor disease can be divided into 2 types of tumors that are not deadly (benign) and tumors that are deadly (malignant) or better known as cancer [1]. Early treatment for patients with brain tumors is crucial considering that the longer the tumor spreads, the more tissue from the organs of the body will be negatively affected [2]. To overcome this, research on brain tumors has been carried out by various researchers, from the identification stage to the classification stage. For research on segmentation, it focuses on how a method can extract the area of the tumor accurately and precisely, while research on the classification of brain tumors focuses on grouping tumor types, whether the tumor contained in the medical image is a benign tumor or a malignant tumor. Research on brain tumors has been proposed and the object used as a research object is magnetic resonance imaging (MRI) images [3] this was chosen because MRI images provide clearer information compared to computerized tomography (CT) images which are visually more likely to be damaged by noise [4]. The difference between the two tumor types is that low-grade glioma (LGG) tends not to actively spread to the surrounding area, and so is the reverse for the high-grade glioma

(HGG) type [5]. The classification method used to classify data according to its class is countless in number and variation, ranging from the simple to the most modern, which technically can group data into several classes [6]. However, sometimes using a simple classification method causes a classification error which is indicated by a low accuracy value, while the use of modern classification methods such as deep learning and neural networks does produce high accuracy values with low error rates, but all of that is exchanged for time and computing costs are expensive because reliable hardware is needed to run deep learning or neural network-based classification methods [6]. Apart from the factor of the selected classification method, the feature extraction method also plays a big role in determining the accurate classification results, if the feature extraction method used does not match the MRI image it will only cause an additional burden for the classification algorithm to determine the class of an image, so knowledge is needed. sufficient to avoid errors in choosing the feature extraction algorithm [2].

Brain tumor classification has become an interesting study from the last few years, Gurbină *et al.* [7] proposed the classification of brain tumors by utilizing several wavelet transformation algorithms to evaluate which algorithm is best for extracting feature values to then be classified using the support vector machine (SVM) algorithm. The wavelets used include Haar, Symlet, Morlet, and Daubechies. In [8] combined several wavelet transformation algorithms to extract features from the MRI image, the types of wavelets used in this study include discrete wavelet transform (DWT), haar wavelet tranform (HWT) and symlet wavelet transform (SWT), and then classified using the SVM algorithm, resulting in a combination of the three wavelets with 50 coefficients to obtain the highest accuracy of 98%. Research conducted by Krishnakumar and Manivannan [1], uses a Gabor filter to improve the quality of MRI images then uses the oversaturated freeway flow algorithm (OFFA) algorithm as a feature extraction algorithm and modified SVM kernel as a classification algorithm, the kernels used for the SVM algorithm include linear, polynomial, quadratic and the sigmoid kernel. The DWT and gray-level co-occurrence matrix (GLCM) algorithms are also used in Ansari *et al.* [9], where the DWT algorithm is used to decompose the image, then the GLCM algorithm Mathew the features from the MRI image, then these features are classified using the SVM algorithm.

The classification carried out on MRI images can include the segmentation stage as well, this is so that the extracted features are only features of the tumor, as in the study of Srinivas and Rao [10] which added a segmentation stage to the MRI image classification method to distinguish between benign and malignant tumors. The segmentation algorithm used is FCM and for feature extraction, it uses 3 levels Daubechies DWT and GLCM and the principle component analysis (PCA) algorithm to select the features that have been obtained, then the SVM algorithm. The segmentation method is also included in the research of Mehrotra *et al.* [11] which uses morphological operations to detect tumor areas then extracts tumor features using the DWT and GLCM algorithms, as well as the PCA algorithm to reduce the size of the image. Further research on the classification of HGG and LGG tumors was carried out by Polly *et al.* [12] by relying on the k-means algorithm for tumor segmentation and DWT for feature extraction and the PCA algorithm as feature reduction and the SVM algorithm as a method for classification between HGG and LGG. The use of the DWT algorithm is also intended to eliminate noise in MRI images.

The use of the DWT decomposition algorithm is quite popular and is also applied to the research of Ismael and Qader [13] which is used to extract features from T1 MRI images, Gabor filters are also used to extract statistical features from MRI images, then the classification used is a neural network with 270 input neurons, 90 neurons hidden layer, and 3 neurons output layer. Latif *et al.* [14] used a multilayer perceptron to classify HGG and LGG tumors. The feature extraction algorithm used was 3 levels of DWT with a total of 152 features. The classification was carried out on the 2015 BraTS image with multimodal properties. Latif *et al.* [15] also proposed a classification method using the random forest method and the CWT and DWT feature extraction algorithms. Wavelet transformation is one of the main features used in classifying brain tumors, as in the study of Amin *et al.* [16] who used the Gabor wavelet transform and the linear binary pattern (LBP) feature to determine tumor and non-tumor MRI. In his research, potential field clustering was used to segment brain tumors first, then the feature extraction algorithm was applied to the segmented image. Amin *et al.* [17] also published a research article on the classification of brain tumors using CNN and using the DWT feature extraction algorithm with Daubechies kernel, then to remove noise, a partial differential diffusion filter was used.

In this study, we proposed classification of brain tumors by relying on machine learning methods as a tool to determine whether the tumors contained in the MRI image belong to the LGG or HGG groups using SVM based on DWT and feature extraction are GLCM and LBP. Our proposed method combined two feature extraction algorithm that is widely used in such field of study. As explained above, none of the previous research, as mentioned in related research, combined the LBP and GLCM for extracting feature out of MRI image. We came up with the main idea to make a simple method that can classify LGG and HGG tumor accurately without trade in a big computational cost.

2. RESEARCH METHOD

2.1. Discrete wavelet transform

DWT is a decomposition algorithm, which decomposes an image based on a set of discrete sets of values from wavelets [8], [17]. The advantage of DWT with the Fourier transform is that the DWT method can obtain 2 feature information at once, namely the frequency and location of the image. The result of the DWT decomposition process is the wavelet coefficient of the image which contains local image frequency information, in other words, DWT can extract the spatial frequency into a time-based frequency field [18], [19]. The use of DWT on MRI images helps in the process of eliminating noise in MRI images at the image signal level [7]. The type of wavelet used in this study is the symlet transform, which decomposes the image symmetrically and does not have a scale function [20]. In 2D images, the DWT algorithm decomposes the image into several sub-bands which are often called low-low (LL), low-high (LH), high-low (HL), and high-high (HH). Each sub-band has its representation, for LL represents the overall coefficient of the image, while LH represents the horizontal coefficient of the image, HL represents the vertical coefficient of the image, and HH represents the diagonal coefficient of the image. In this study, the LH sub-band was used to extract features from the MRI image. The calculation of the coefficients of the DWT algorithm is in (1). Where s is the signal from the image, $a_{i,j}$ is the estimated component of the wavelet, while $d_{i,j}$ is the detailed component representation of the wavelet. $H(s)$ is the high pass filter obtained from the original wavelet image, while $L(s)$ is the low pass filter, 'i' and 'j' are components of wavelet measurement and translation parameters of the image.

$$DWT(s) = \begin{cases} a_{ij} = \sum f(s)H(s) \times i(s-2ij) \\ d_{ij=} \sum f(s)L(s) \times i(s-2ij) \end{cases} \quad (1)$$

2.2. Support vector machine

The SVM classification method is a reliable classification method in classifying data by providing a feature set on the SVM algorithm [21]. SVM groups data by forming a hyperplane that divides 2 groups of data according to the class. In this study, SVM was used to group MRI images into 2 classes, namely MRI images with benign tumors and MRI images with malignant tumors. The SVM algorithm [22], [23] has a great deal of flexibility given through the kernel functions used to prepare the processed data. Polynomial kernels were used in this study to classify benign tumors and malignant tumors on MRI images. Given a training set of images in class $C = \{C_1, C_2, C_3, \dots, C_n\}$ where $C \subset B^n$ is the mapping function of $\emptyset : C \to B$ is the feature space. The SVM concept [22] was invented by Cortes and Vapnik in 1995 as in (2). Where $C.\emptyset \geq R - \gamma$, with $p = 1,2,3, \dots, n$ and $\gamma_p \geq 0$, R is the bias and sample, γ is a variable slack.

$$min \left[\frac{1}{2}\right] \|C\|^2 + \frac{1}{2} \sum_{n=1}^{1} \gamma_p - R \quad (2)$$

2.3. Gray level co-occurrence matrix

The GLCM feature extraction method is widely used to extract texture features from an image [24]. By analyzing the texture of the MRI image, we can find out the information contained in the MRI image, for example, if an MRI image of the brain has a benign tumor or a malignant tumor. The GLCM feature extraction method [25], [26] is one of the simplest methods of extracting features from an image but is still reliable in extracting important features from an image. GLCM can be described as a 2-dimensional histogram that calculates the frequency of occurrence of the x value along with y, the GLCM method calculates the frequency of occurrence of the x and y values at a specified distance S and orientation. The angles of the GLCM algorithm used in this study are 0, 45, 90, and 135. From each corner property, 4 features are extracted from the MRI image, so a total of 16 features are obtained for 1 MRI image. The features extracted in this study include contrast, correlation, energy, and homogeneity. Contrast is determined by observing the pixel intensity value in neighboring pixels of an image. Contrasts are represented using (3) with $f(x,y)$ is the coordinate of the image pixels. Correlation is an image feature that can be described as a spatial dependence between one pixel and another. The value of the correlation feature is at a distance of [-1, 1] and is obtained from the (3) where M is the mean of the image and σ is the standard deviation of the image as in (4). Energy can be defined as the number of occurrences of the same pixel pair, and energy is obtained from (5). Homogeneity measures the level of local homogeneity in an image, obtained by (6).

$$contrast = \sum_{x=0}^{i=1} \sum_{y=0}^{j-1} (x-y)^2 f(x,y) \quad (3)$$

$$correlation = \frac{\sum_{x=0}^{i=1} \sum_{y=0}^{j-1} (x,y) f(x,y) - M_x M_y}{\sigma_x \sigma_y} \quad (4)$$

$$energy = \sqrt{\sum_{x=0}^{i=1}\sum_{y=0}^{j-1} f^2(x,y)} \quad (5)$$

$$homogeneity = \sum_{x=0}^{i=1}\sum_{y=0}^{j-1} \frac{1}{1+(x-y)^2} f(x,y) \quad (6)$$

2.4. Linear binary pattern

In classification, determining the features used is important in obtaining accurate classification results. Features extracted from an MRI image should differ from one image class to another image class, this is so that when the features are used to determine what class an MRI image belongs to, the results obtained are not ambiguous so that the accuracy results of the classification method can be satisfactory. In this paper, LBP feature extraction is used as a statistical feature extraction [6], [27]. LBP feature extraction is widely used in the field of computer vision research, especially those using images as data [28], [29]. The basic concept of the LBP method is to compare the neighboring pixel with the middle pixel and the middle pixel of the observation area to the threshold value. If the neighboring pixel has a value higher than the center pixel of the observation area, it is given a value of 1, and vice versa. The LBP feature [16] is obtained from the binaryization stage between 2 neighboring pixels as in (7). Where in $LBP_{P,R}$, R is the neighboring radius which determines the distance between the middle pixel and its neighboring pixels, P is the number of neighboring pixels processed [30], X_p is the neighboring pixel intensity and X_c is the central pixel value. From the LBP feature extraction algorithm, 10 features are obtained from 1 MRI image.

$$LBP_{P,R(X_c)=\sum_{P=0}^{P-1}\mu(X_p-X_c)^{2^P}} \quad (7)$$

$$where\ \mu(y) = \begin{cases} 1, y \geq 0 \\ 0, y < 0 \end{cases} \quad (8)$$

2.5. Proposed method

The program begins with training on MRI image data which can be seen in Figure 1, on the left section, where MRI image features are extracted using the LBP and GLCM algorithms and applying DWT. In Figure 1 on the right section, is the testing stage with the same process as the training stage, only at the bottom of Figure 1, it is a match between the features that have been extracted in the testing phase with the model obtained from the SVM algorithm, then proceed with the performance evaluation stage of the proposed method. The first step for both training and testing sequences is cropping the MRI image to make sure the features that will be later extracted using LBP, GLCM, and DWT are spot on to the tumor area. As for the cropping dimension, we are observing our dataset very carefully and decide the right dimension to crop the image, the result of cropping the MRI image as shown in Figure 2(a) dan Figure 2(b). Then for both training and testing sequence, the decomposition using DWT was applied to every image followed by a feature extraction process using LBP and GLCM. As for the sub-band we are using from the decomposition result of DWT, we decided to use the low-high sub-band. After the decomposition process, the image proceeds to feature extraction process using LBP and GLCM, for the parameter for both algorithms is already mentioned above. The result of the training sequence is a model that maps the feature of the MRI image whether the image belongs to an LGG or HGG tumor. Then the classification model is used for classifying the feature that is already extracted from the testing sequence, then the evaluation process is carried out to measure the performance of the proposed method.

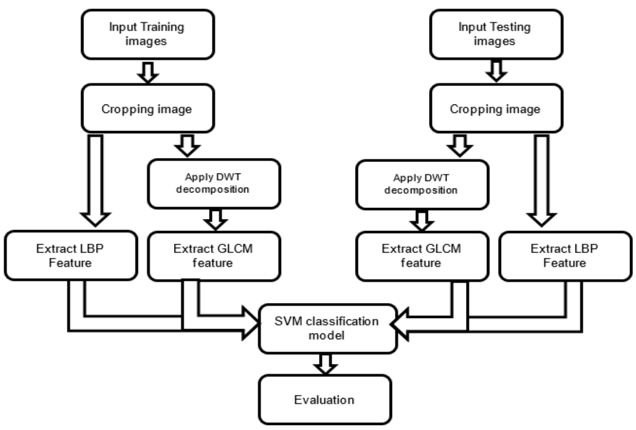


Figure 1. Proposed method

3. RESULTS AND ANALYSIS

This study uses MRI images obtained from BRATS 2015, BRATS 2019, and the website www.radiopaedia.org with the search keyword "low-grade tumors", with a total of 210 images used with 2 classes, HGG and LGG. Image data partition for training is 68 HGG images and 68 LGG images, and for the test data for HGG and LGG, respectively are 37 images. The MRI image used in this study used the axial MRI image with Fluid-attenuated inversion recovery (FLAIR) modality. MRI with FLAIR modality was chosen because of the difference in contrast that is seen between the normal brain and brain tumor affected [30]. The image size used is 512×512 pixels as shown in Figure 2. In the classification process, the image will be cropped to a size of 317×311 pixels as shown in Figure 2. From the results of the experiments we have done, cropping the image increases the accuracy of the classification method.

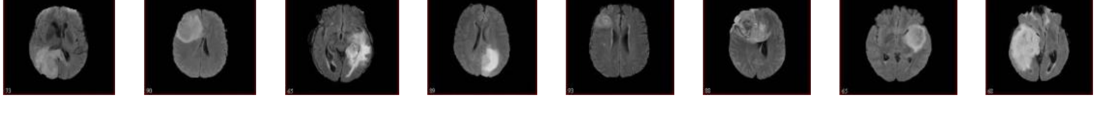
DWT algorithm used to decompose the MRI image into 4 sub-bands. In this study the LH sub-band is used, then from that sub-band, the GLCM algorithm extracts 16 features based on a predetermined angle. LBP algorithm extracts the features from the MRI image and produces 10 features. After all feature extraction algorithms have been run, the SVM algorithm is used to form a model which will later be used as a reference for testing MRI images. The SVM method is validated using k-fold cross-validation with a value of $k = 10$. The research we conducted was tested using a confusion matrix with 4 properties, true positive (TP), true negative (TN), false negative (FN), and false positive (FP). $True\ Positive\ =\ MRI\ HGG$ images detected as MRI HGG. $True\ Negative\ =\ MRI\ LGG$ images detected as MRI LGG. $False\ Positive\ =\ MRI\ LGG$ images detected as MRI HGG. $False\ Negative\ =\ MRI\ HGG$ images detected as MRI LGG. In Table 1, we also included specificity, sensitivity, and accuracy performance calculations using (9)-(11).

$$specifity = \frac{TN}{TN+FP} \tag{9}$$

$$sensitivity = \frac{TP}{TP+FN} \tag{10}$$

$$accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{11}$$

According to Table 2, it can be seen that there is 1 LGG MRI image that is incorrectly grouped into the HGG MRI image, while for the HGG MRI image there is no miss-grouped image. The accuracy results obtained from the classification method that we proposed are 98.6486. There are interesting things that can be found in the Table 2, wherein the experiments we conducted were when using the HL sub-band, the accuracy results we obtained reached 100%. However, when we used 3 DWT levels with the HL sub-band, the result obtained accuracy fell to 98.6486. Therefore, in this study, we used the LH sub-band as a feature for our classification, because the results were consistent. We also conducted experiments at the level of the DWT algorithm that we used, using 2 levels and 3 levels of DWT, we re-evaluated the performance results of the method we proposed and the results we obtained are in Table 2. Our comparisons are based on the results of a literature review on previous research that used 2 levels or 3 DWT levels, as well as to determine the consistency of the accuracy results obtained from our method. Whereas, according to Table 3, an interesting result is obtained from the experimental results using 3 DWT levels. It can be seen that the results from the Table 2 show that the use of 3 DWT levels gets the same results as 1 DWT level using the LH sub-band. In addition, we also measure the time required to classify images using 1 level and 3 DWT levels. We tested 20 run tests as seen in Figure 3, the results are in the Table 3, for each DWT level, and the results obtained for 1 DWT level require an average time of 13.06534465 for 20 trials, and for 3 DWT levels it takes an average 10.6606, it can be concluded that 3 DWT levels are faster in classifying MRI images with a difference of 2.4047482 seconds with a consistent classification accuracy that does not change. This can occur because the MRI image decomposed using 3 DWT levels is smaller than when using 1 DWT level, from the 512×512 size MRI image when subjected to the 1 level DWT algorithm, each sub-band of DWT forms an MRI image feature measuring 189×159 pixels, and for 3 DWT levels each sub-band measuring 52×45 pixels, this affects the length of feature extraction by the GLCM algorithm where the larger the image dimensions, the longer the process.



(a) (b)

Figure 2. Examples of (a) HGG and (b) LGG images

Table 1. Confusion matrix

Predict class	Actual class	
	HGG	LGG
HGG	37 (TP)	0 (FN)
LGG	1 (FP)	36 (TN)

Table 2. Classification using different level and sub-band

Varian	Specificity	Sensitivity	Accuracy
1 level DWT, HL	1.000000	1.000000	100
1 level DWT, LH	0.97297297	1.000000	98.6486
3 level DWT, HL	0.97297297	1.000000	98.6486
3 level DWT, LH	0.97297297	1.000000	98.6486

Table 3. Classification using different level DWT

Varian	Specificity	Sensitivity	Accuracy
1 level DWT	0.97297297	1.000000	98.6486
2 level DWT	0.891891891	1.000000	94.5946
3 level DWT	0.97297297	1.000000	98.6486

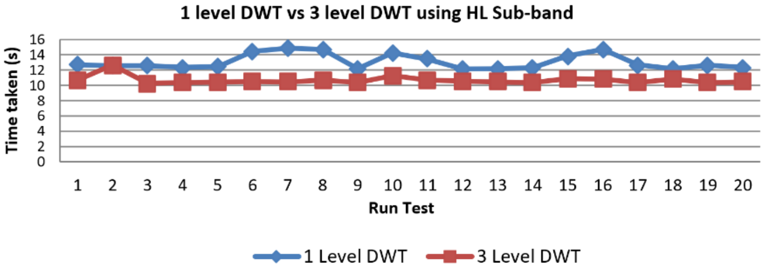
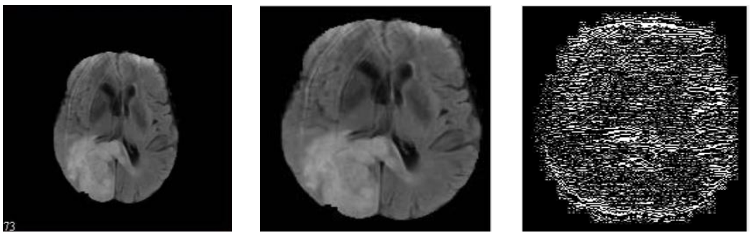


Figure 3. Comparison time is taken for different DWT level



(a) (b) (c)

Figure 4. Samples image from preprocessing steps: (a) original HGG MRI image, (b) cropped HGG MRI image, and (c) low-high sub-band of DWT

Based on Figure 4(a), the sample original image in HGG has been displayed and several image in form HGG as shown in Figure 2. Figure 4(b) shown the next step after original image. Cropped aims to focus the detection area on the object. The next step after cropping is implement DWT sub-bands. Figure 4(c) displayed sample of result in low-high sub-band of DWT.

It can be seen that the specificity value has decreased because 4 LGG MRI images are incorrectly classified into the HGG MRI image class. This result is because the decomposed image through the DWT algorithm experiences down-sampling, so that the features of the MRI image are not globally covered, at least in the research we conducted with the parameters of our proposed method. The performance of our proposed method with other similar studies has been compared as shown in Table 4. As for our comparison parameters with the other researchers are the similar method that are used for feature extraction and classify the brain tumor. Latif *et al*. [14] used three-level DWT with several classifier methods such as SVM, random forest, and multi-layer perceptron, as for Amin *et al*. [16] he used LBP feature extraction with Gabor wavelet transform and SVM with quadratic kernel for classifier, lastly Mishra and Deepthi [8] proposed a SVM based classification method with some coefficient selection with 25, 50, and 75 coefficient variables. This research wants to show that using the optimal feature selection and classification method can actually provide a same or better performance in term of classification accuracy than several previous proposed methods.

Table 4. Comparative analysis with several previous method

	Latif [14]	Amin [16]	Mishra [8]	Proposed method
Accuracy (%)	96.38	97	98	98.64

4. CONCLUSION

Research on the classification of brain tumors is an interesting and challenging research topic. The use of the DWT and SVM algorithms as feature extraction and classification methods is the choice in those studies because based on the results of the previous research, the two algorithms are reliable in classifying brain tumors. The difference between this study and other studies is the addition of LBP feature extraction, and the result is a high accuracy of 98.6486%, higher than some of the previously proposed methods. For method development, it can be emphasized on adding a segmentation stage to the feature extraction process flow, so that the features obtained are more focused on the tumor area.

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