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A HYBRID CLASSIFICATION APPROACH BASED ON MORPHOLOGICAL SEGMENTATION FOR CLASSIFYING MRI BRAIN DISEASES

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Abstract. *Recently, the ageing population is increasing rapidly and degenerative brain disease is one of major diseases for older people. In practice, magnetic resonance (MR) imaging is one of most advanced medical imaging methods to diagnose brain disease. Automatic and semi-automatic brain MR images segmentation have been used to process and classify medical images. However, there are two major drawbacks in previous segmentation methods: (1) automatic segmentation is limited to the treatment of some certain types of images; (2) single segmentation method has its disadvantage and restriction on segmentation. To overcome the drawbacks, this study proposed a hybrid semi-automatic segmentation method. Firstly, proposed model uses segmentation algorithm to segment regions of interest (ROI) of brain. Secondly, wavelet transform is utilized to deconstruct and calculate the feature value. Thirdly, normal and abnormal brain images are classified by classification algorithm. Experimental results show that the proposed model with shape filter datasets (77.32-80.13%) is evidently higher than without shape filter (56.44-58.37%). In practice, advantages of proposed method are as follows: (a) reduce medical personnel's workload; and (b) provide more appropriate diagnosis and treatment for patients.*

Keywords: Magnetic resonance imaging, Wavelet packet transform, Support vector machine, Segmentation, Brain diseases, Intelligence system

1. **Introduction.** Nowadays, healthcare technology is enhanced rapidly and mortality declines and then people live longer. For older people, major disease pattern has also changed to "delayed degenerative diseases". People gradually concern about the degenerative brain disease, such as Alzheimer's disease (AD) and mild cognitive impairment (MCI) diseases. Recently, researchers used magnetic resonance imaging (MRI) to help research [1] and the research indicates Alzheimer's disease may find the omen of the onset in young people. Magnetic resonance imaging (MRI) is an advanced method for medical imaging detection, and its operation mode is different from the general medical imaging such as X-ray, radioisotope and computed tomography (CT). MRI utilizes the principle of the magnetic field, radio waves, resonance, and does not use radiation. In addition, there are three advantages in MRI: (1) excellent imaging resolution to the soft tissues; (2) non-invasive; and (3) non-radioactive. Therefore, MRI has become a popular brain imaging technique now. Based on the advantages mentioned above, MR images will be used as experiment datasets to detect brain disease in this paper.

In the processes for using MR images to diagnose brain disease, image segmentation is an important pre-processing step. The purpose of image segmentation is the separation of the desired elements with the elements that have the same properties in a set from the other elements of the image [2]. The most frequently used techniques in medical image segmentation can be classified into five categories: region-based method, thresholding based method, edge-based method, classification-based method, and hybrid techniques. However, the first four methods have their shortage as follows. (1) In region-based method, the application of any region growing process can lead to three kinds of errors: (a) a boundary is not an edge and there are no edges nearby; (b) a boundary corresponds to an edge but it does not coincide with it; (c) there exist edges with no boundaries near them [3]. (2) In thresholding-based method, these techniques neglect all the spatial relationship information of the images; they are inefficient for images that blur at object boundaries, or for multiple image component segmentation [4]. (3) In edge-based method, the derivative nature of this approach makes them extremely sensitive image noise level. Significant amount of processing is required to remove noisy edges [5]. (4) In classification-based method, the performance of the classification-based segmentation strictly depends on inputs of the classifier and training parameters [6]. Recently, many studies focus on hybrid techniques, because researcher finds that the hybrid techniques which integrate the results of boundary detection and region growing are expected to provide more accurate segmentation of images [7].

Generally, the medical images are segmented by specialists; with different specialists, the segmentation results will be different based on their past experiences and training process. In addition, manual segmentation is time and manpower consuming, even if the same image, the result generated by the same specialist's judgment may be different because of their mental condition. Recently, many automatic and semi-automatic segmentation methods have been developed by researchers. Automatic segmentation method does not need any human interaction and it is time-saving in the process. However, there are some restrictions on the automatic segmentation, and automatic segmentation mostly is utilized in two applications: (1) a specific type of image; (2) the general types of images [8]. Conversely, the merit of semi-automatic segmentation could be applied the same segmentation method in any image, without restrictions on the image types [8]. Further, by using MRI to detect brain disease, we can see that the gray-level values of abnormal brain tissues are quite different in the normal ones on volume and intensities. Different features in different brain images will increase the complexity of the segmentation. Therefore, how to find out the interested area of the images is a challenging task, and it is a critical step for feature selection and classification.

As mentioned above, there are two drawbacks in previous methods: (1) the automatic segmentation is restricted in specific contours; and (2) single segmentation method has its own insurmountable disadvantage. To reconcile the drawbacks, this paper proposed a semi-automatic segmentation method to improve the restriction in the automatic segmentation and increase the accuracy of classification. i.e., we used the concept of hybrid techniques and combined different segmentation methods to enhance the segmentation performance.

The remainder of the study is organized as follows. Section 2 describes the literature reviews and related works. In Section 3, we present the concept of proposed procedures, and introduce the proposed algorithm step by step with example images. Section 4 describes the experiment results, verification and finding. Finally, the conclusion is in Section 5.

2. **Literature Reviews.** This section will briefly review the related literature which includes MR image, brain diseases, segmentation techniques, morphological operation, wavelet packet transform, support vector machine (SVM), sequential minimal optimization (SMO), and classification and regression trees (CART).

2.1. **Magnetic resonance imaging and brain diseases.** According to latest research reports, MRI is a very important technique to find out the potential patient of Alzheimer's disease. Through scanning brain of healthy people, researchers find that people who have more atrophy in the specific part of the cerebral cortex, the chance to suffer from the Alzheimer's disease is three times higher than the normal ones [9]. And the other important part is brain tumor; the more dangerous tumor of brain is optic pathway gliomas (OPGs). OPGs growth may cause severe complications depending on location, size and characteristics [10].

Nuclear magnetic resonance imaging (NMRI) is also known as spinning imaging and magnetic resonance imaging (MRI). Almost all of the body tissues can perform MRI examination and it is especially clear and delicate in the soft tissue imaging; therefore, this technology is far beyond any other medical imaging systems. For this reason, MRI would be used as experiment datasets to diagnose brain disease by the proposed model.

2.2. **Segmentation techniques.** Segmentation has taken an important role in medical image processing, and a reliable segmentation method will highlight an important part of image. Recently, many medical image segmentation research papers have been published [11-13]. The common MRI segmentation techniques can be divided into five categories: Region-based method, thresholding method, edge-based method, classification-based method, and hybrid techniques. Region-based method such as region growing algorithm, it initiates with a seed point, through the examining of average gray-level, the texture and other properties, the pixels with similar properties will be included in each area. The region growing algorithm was used by region-based method [14]. Thresholding-based method distinguished the object and the background primarily based on setting a threshold value. However, the method was inefficient for images that blur at object boundaries, or for multiple image component segmentation [4]. Edge-based algorithm performed the segmentation with all kinds of edge detection filters such as Sobel and Laplace detector. However, the derivative nature of this approach made them extremely sensitive image noise level [5].

Classification-based algorithm operated as self-organizing map (SOM) [15] and fuzzy c-means (FCM), classification-based method needs to do training first and the performance mainly depended on training parameters and the inputs of the classifier [6]. Hybrid techniques [7] integrated boundary detection and region growing method to get better segmentation. From literature reviews, hybrid technique can integrate different methods to improve the shortage of single method. To take the advantage of hybrid method, this paper would apply hybrid segmentation to the proposed model.

2.2.1. *Morphological operation.* Morphological operation has two basic operations: dilation and erosion. Dilation is utilized in expanded sub-images boundaries of pixels and defined as symbol θ. Opposite erosion is employed in reducing sub-images boundaries of pixels and defined as symbol $\oplus$. And the advanced operation methods are opening and closing. Opening operation uses both of two basic operations. Firstly, use erosion for reducing all undesired pixels or line. Second, use dilation operation to recover image. If A is an image and B is a structuring element, opening defined A is eroded by B; therefore, the slim or narrow parts will be reduced. Then dilation will dilate erodent A by B for smoothing boundaries and removing small protrusions. The opening operation is defined as symbol $\circ$ and its computation is shown as Equation (1). Closing is opposite operation in opening operation, firstly is dilation and secondly is erosion. It can link boundaries for integrated boundaries. The closing operation is defined as symbol $\bullet$, and its computation can be shown as Equation (2).

$$A \circ B = (A \theta B) \oplus B \tag{1}$$

$$A \bullet B = (A \oplus B) \theta B \tag{2}$$

2.2.2. *Binarization operation.* The concept of Otsu's algorithm was proposed by Otsu [16], Otsu's algorithm is exhaustively searching for the threshold that minimizes the intra-class variance (the variance within the class), and a weighted sum of variances of the two classes is defined as Equation (3):

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \tag{3}$$

Weights w_i are the probabilities of the two classes separated by a threshold t and σ_i^2 variances of these classes.

Otsu showed that minimizing the intra-class variance is the same with maximizing inter-class variance defined as Equation (4):

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = w_1(t)w_2(t)[\mu_1(t) - \mu_2(t)]^2 \tag{4}$$

which is expressed in terms of class probabilities w_i and class means μ_i.

The class probability $w_1(t)$ is computed from the histogram as t, and it is defined as Equation (5):

$$w_1(t) = \sum\nolimits_0^t p(i) \tag{5}$$

And the class mean $\mu_1(t)$ is defined as Equation (6):

$$\mu_1(t) = \sum\nolimits_0^t p(i)x(i) \tag{6}$$

where $x(i)$ is the value of the center in the ith histogram. Similarly, it can compute $w_2(t)$ and μ_t on the right-hand side of the histogram for bin greater than t.

2.3. **Wavelet packet transform.** The concept of wavelet was proposed by Haar in 1910 [17]. Until 1986, Meyer [18] proposed the discrete wavelet transform and Mallat [19] introduced the concept of multi-resolution to the wavelet and constructed the wavelet representation. The wavelet decomposition functions at level m and time location t_m can be expressed as Equation (7):

$$d_m(t_m) = x(t)\psi_m\left(\frac{t - t_m}{2^m}\right) \tag{7}$$

where ψ_m is the decomposition filter at frequency level m. The effect of the decomposition filter is scaled by the factor 2^m at stage m; otherwise the shape is the same at all scales [20].

The main advantage of wavelet is that they have a varying window size, being wide for slow frequencies and narrow for the fast ones; thus it results in an optimal time-frequency resolution in all the frequency ranges [21]. Wavelet packet analysis is an extension of the discrete wavelet transform (DWT) [22]. The advantage of wavelet packet analysis is that it is possible to combine the different levels of decomposition in order to achieve the optimal time-frequency representation of the original [21]. To consider the advantage of wavelet packet, proposed model would use wavelet packet to decompose the signals of segmented ROI.

2.4. **Classification algorithm.** This section will review the classification algorithms used in proposed method: support vector machine, sequential minimal optimization (SMO), and classification and regression trees.

2.4.1. *Support vector machine and sequential minimal optimization.* Support vector machine (SVM) was proposed by Vapnik and Cortes [23]. The linear SVM algorithm is described as Equation (8) and Equation (9):

$$\min_{w,\xi,b}\left\{\frac{1}{2}w^2+c\sum_{i=1}^{n}\xi_i\right\} \tag{8}$$

subject to (for any $i=1,\ldots,n$), $y_i(x\cdot x_i-b)\geq 1$

$$\min_{w,\xi,b}\max_{\alpha,\beta}\left\{\frac{1}{2}||w||^2+c\sum_{i=1}^{n}\xi_i-\sum_{i=1}^{n}\alpha_i[y_i(w\cdot x_i-b)-1+\xi_i]-\sum_{i=1}^{n}\beta_i\xi_i\right\} \tag{9}$$

Nonlinear SVM classification [24] applied the kernel function in SVM. The resulting algorithm is formally similar, except that every dot product is replaced by a nonlinear kernel function. This allows the algorithm to fit the maximum-margin hyperplane in a transformed feature space. The transformation may be nonlinear and the transformed space with high dimension; thus though the classifier is a hyperplane in the high-dimensional feature space, it may be nonlinear in the original input space. There are four common kernel functions define as Equations (10)-(13):

$$\text{Polynomial (homogeneous): } k(x_i,x_j)=(x_i,x_j)^{\alpha} \tag{10}$$

$$\text{Polynomial (inhomogeneous): } k(x_i,x_j)=(x_i,x_j+1)^{\alpha} \tag{11}$$

$$\text{Gaussian radial basis function: } k(x_i,x_j)=\exp(-\gamma||x_i-x_j||^2),\ \text{for } \gamma>0 \tag{12}$$

$$\text{Hyperbolic tangent: } k(x_i,x_j)=\tanh(kx_i\cdot x_j+c) \tag{13}$$

SVM is a robust classifier, and can deal with hyperplane, incomplete, ambiguous and uncertain information without prior knowledge. SVM has been widely used as a useful tool for classification in medical image research fields [25,26]. For this reason, SVM would be utilized to classify normal and abnormal brain MRI datasets in this paper.

Sequential minimal optimization (SMO) is an improved training algorithm and efficiently solves the optimization for SVM, SMO decomposes the problems into a set of smallest possible problems, and the set of problems can be solved and analyzed. SMO can be modified to solve fixed-threshold SVM [27]. SVM involves the Lagrange multipliers and the set of problems involves two Lagrange multipliers in SMO; hence each α_1 and α_2 were reduced the constraints as Equation (14):

$$0\leq\alpha_1,\alpha_2\leq C,\quad y_1\alpha_1+y_2\alpha_2=k \tag{14}$$

2.4.2. *Classification and regression trees.* Classification and regression trees (CART) is proposed by Breiman et al. in 1984 [28]. CART is a non-parametric decision tree learning technique that produces either classification or regression trees, depending on whether the dependent variable is categorical or numeric, respectively. CART is used in disease diagnosis [29], finance research field [30] and other applications [31]. Classification tree was built in accordance with splitting rule – the rule that performed the splitting of learning sample into smaller parts. It already knows that each time data have to be divided into two parts with maximum homogeneity. Classification tree could be shown as Figure 1.

Let t_p be a parent node and t_l, t_r denote left and right child nodes of parent node t_p respectively. Consider the variable matrix X of learning sample with M number of

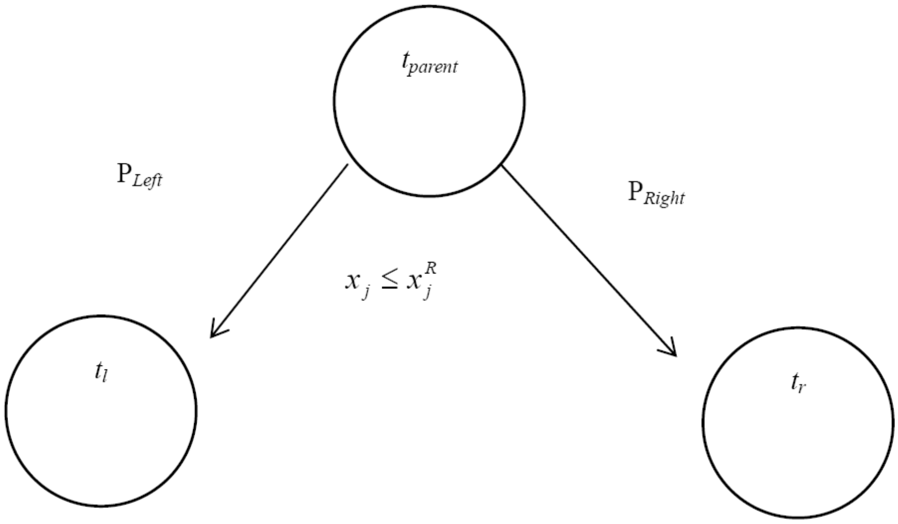


FIGURE 1. Splitting algorithm of CART

variables x_j and N observations, and x_j^R denotes the best splitting value of variable x_j. Let class vector Y consist of N observations with total amount of K classes.

3. **Proposed Model.** In this section, proposed concepts and algorithms of the proposed model are described.

3.1. **Proposed concepts.** In the past, manual-segmentation medical image was usually done by doctors or radiological technologist. However, the segmenting results generated by different specialists were different in the same image. The results would cause a miscarriage of justice which cannot be given to the patient appropriate treatment. In addition, due to the results of recently scientific and technological progress, the number of medical imaging is explosive growth and the existing manpower will be unable to cope with such a high workload. The problem will result in the waste of medical resources and increase social costs. Therefore, automatic and semi-automatic segmentation are proposed to solve the problem. The advantages of automatic segmentation method are saving time and effort, but disadvantage is that it would often be limited as to the specific image [32]. The semi-automatic segmentation is not limited [8] and the same segmentation method can be applied to different images in wider application. In general, segmentation method has several different types. From the related studies, the hybrid technique would be a better method because it integrates different methods to improve the shortage of single method [7]. Thence, this paper would apply hybrid semi-automatic segmentation to the proposed model.

To analyze signals, wavelet packet is an efficient tool and has been applied widely in many researches. Wavelet packet can provide a wider range of possibilities for time-frequency plane and it is possible to combine the different levels of decomposition in order to achieve the optimum time-frequency representation of the original [21]. To take advantage of wavelet packet, wavelet packet would be applied to decompose the signals of segmented ROI. Further, SVM is a kind of robust classifier, and can deal with hyperplane, incomplete, ambiguous and uncertain information without prior knowledge. Recently, SVM has been widely used as a useful tool for classification in many research fields.

Based on explanation above, this study proposed a three stages classification procedure based on hybrid semi-automatic segmentation method to enhance the classification accuracy. The three stages are briefly described as follows.

(1) This paper proposes a hybrid semi-automatic segmentation method which integrates Otus thresholding algorithm and morphology operations to segment the brain ROI as the image pre-processing. The parameters of morphology operations will add human recognitions to enhance the performance and the proposed method will be more suitable on different contours of brain images.

(2) The segmentation results will use the wavelet packet to decompose and calculate the feature values.

(3) Robust classifier, SVM, is used to classify the images into normal and abnormal brain image. CART and SMO [27] are utilized as comparison method to verify the proposed hybrid semi-automatic segmentation method.

3.2. **Proposed algorithm.** In practical operations, the procedure of the proposed method was shown in Figure 2. The detailed algorithm could be introduced step by step in the following.

Step 1: Input the brain MRI

This step employed the open MR images from The Whole Brain Atlas (Harvard medical school website (http://www.med.harvard.edu/aanlib/home.html)) as experiment datasets to illustrate the proposed method. The dataset website contained various anatomical information, curriculum and MR images on brain diseases. This study has collected normal brain T1-weighted MR images and four degenerative diseases T1 weight MR image dataset: mild Alzheimer's disease, mild Alzheimer's visual agnosia, cerebral calcification, and Pick's disease. This step used Matlab software package as image segmentation tools, firstly inputs the T1-weighted MR images datasets, and then the image was converted from RGB (red, green, and blue) to grayscale.

Step 2: Enhance the image edges

In Step 1, the images have been converted to grayscale image and then this step used morphological dilation method to strengthen the image edges. The enhanced image was shown in Figure 3.

Step 3: Create an image mask by binarization

This step used the Otus algorithm [16] to select the threshold value from images and the selected threshold value was used in the binarization parameter for creating mask. Then this step filled the mask to become a complete image mask.

Step 4: Enhance the mask edges

From Step 3, initial mask was created, this step used morphological erosion to remove noise, and further enhanced the mask edge to obtain the final mask as Figure 4.

Step 5: Select images by expert's mask

Firstly the radiologist provides three experts' masks, the three experts' masks have been registered the area of brain MR images. Secondly this step automatically picks up the images of datasets (enhanced mask of dataset by Step 4) by expert's mask, the expert's mask was proportional enlarged, and the width is equal to the mask of dataset. Thirdly, the pixels of difference area were calculated between the expert's mask and the enhanced mask of dataset, and the other two experts' masks were repeated by same process. Fourthly, the average pixel was calculated among three experts' masks and the enhanced masks of dataset. After experiment and inspection, this step finds that if the average pixel is smaller than ten pixels, the images of dataset will be selected automatically and used in segmentation of ROI.

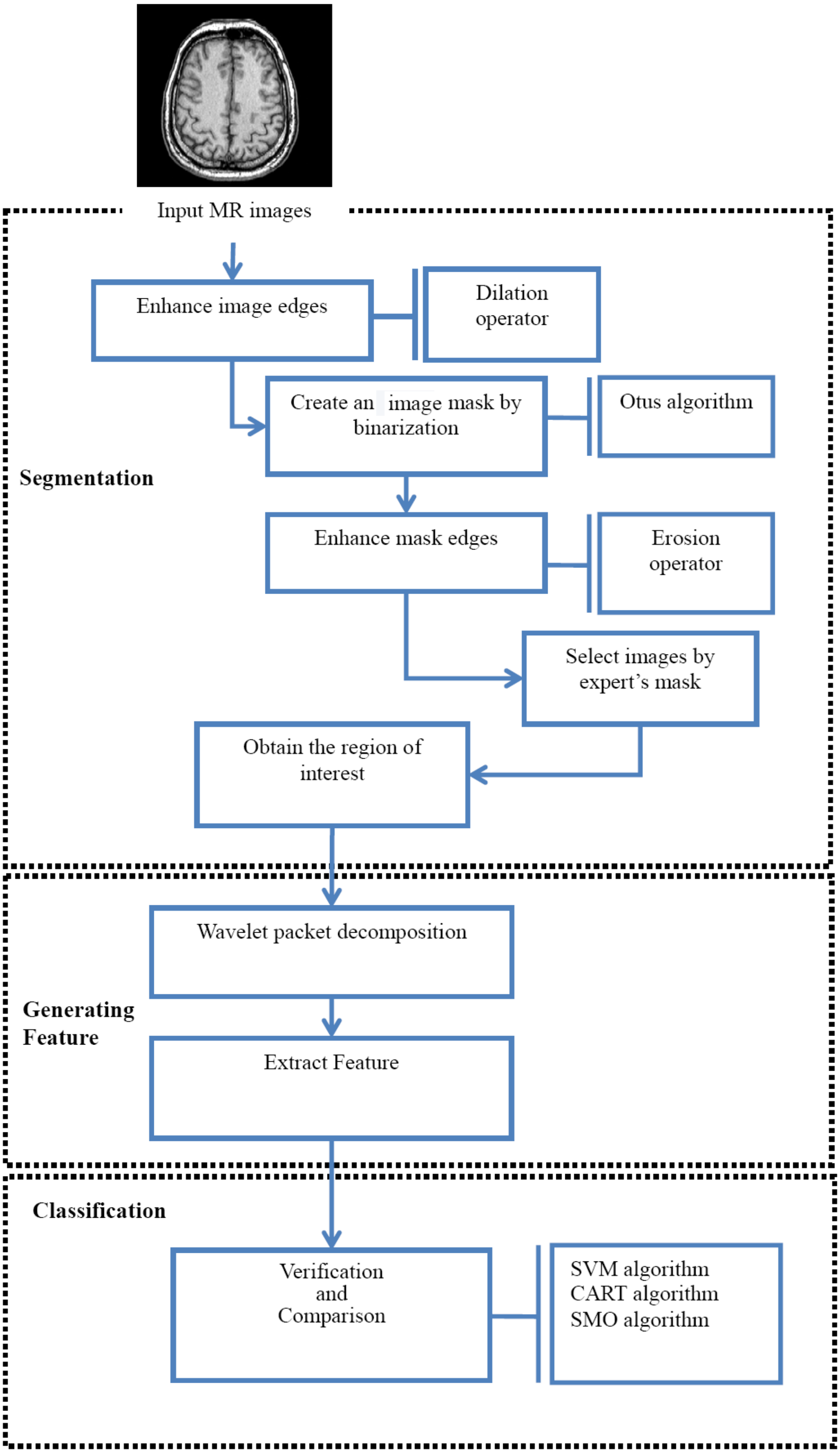


Figure 2. The procedure of the proposed method

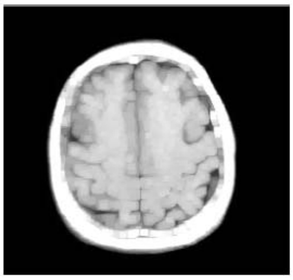


FIGURE 3. The strengthened image edges by morphological dilation operation

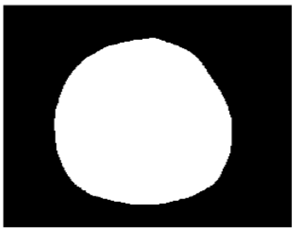


FIGURE 4. The enhanced mask by morphological erosion

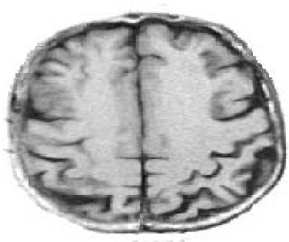


FIGURE 5. The segmented ROI image

Step 6: Obtain the region of interest

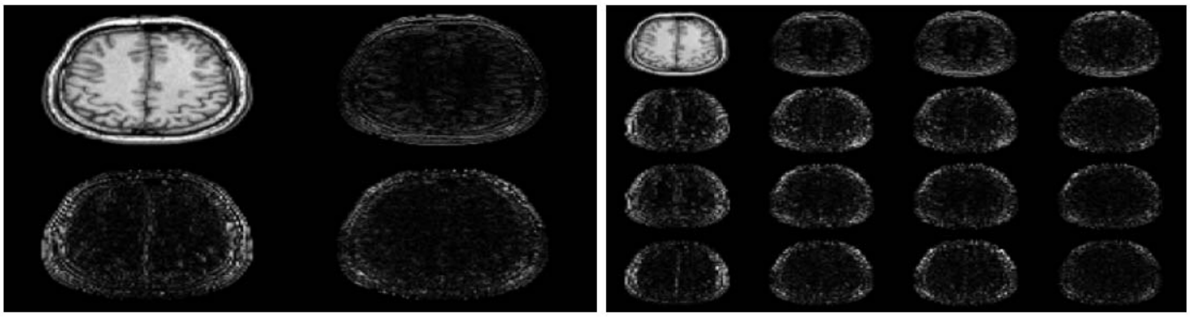
This step multiplied mask using original image in pixel by pixel to filter original image and gets ROI. The segmented ROI was shown in Figure 5.

Step 7: Wavelet packet decomposition

This step utilized bior2.2 wavelet filter to decompose the segmented ROI. The depth refers to the wavelet packet transform of the tree hierarchy; it determines the wavelet packet filter coefficients. This study used depth $d = 1$, $d = 2$ to implement wavelet packet decomposition as Figures 6(a) and 6(b). The depth of 1 will generate four coefficients. The depth of 2 generates 16 coefficients. This study used 20 coefficients from depth $d = 1$ and $d = 2$.

Step 8: Extract attribute

In this step, wavelet packet features were selected and calculated. This step selected the feature value based on Avci [33] method, and used the statistical value as input parameter to classify images. Then the extracted eight features include: mean value, median value, maximum value, minimum value, range value, mode value, standard deviation, and mean absolute value. For example, the mean value was calculated by the average of 20 coefficients of wavelet packet decomposition; similarly, the other feature was computed from 20 coefficients.



(a) depth = 1 (b) depth = 2

FIGURE 6. Wavelet packet decomposition

Step 9: Classify images

In this step, three different classifiers are employed, the eight features extracted in Step 8 as input attributes, then SVM [23], SMO [27] and CART [28] are used to compare with the proposed method in accuracy.

4. **Experiment and Results.** This section provides accuracy evaluation and comparison, to verify the proposed model, datasets from region hospital and The Whole Brain Atlas (Harvard medical school website (http://med.harvard.edu/AANLIB/)) are used as the experiment datasets. Further, some findings are discussed in this section.

4.1. **Evaluation and comparison.**

4.1.1. *Whole Brain Atlas dataset experiment results.* In this section, the open MR images from The Whole Brain Atlas (Harvard medical school website (http://med.harvard.edu /AANLIB/)) is employed as experiment dataset. There are 77 T1-weighted images (63 abnormal and 14 normal) in this dataset. All images are segmented and the ROI is obtained. Eight features are extracted by wavelet packet extraction coefficients. In classification step, the proposed method selects SVM classification algorithm to validate and compare with other classification algorithms.

For verification, 2/3 images are used as the training datasets, and the rest (1/3 images) are selected for testing. This paper repeats the experiments ten times in different sampling, and the results are shown in Table 1. For comparison, this section uses SVM, CART [28] and SMO [27] as comparative methods for classifying normal and abnormal brain images. From Table 1, we can see that SVM (polynomial) method outperforms the listing methods in segmented images and original images.

TABLE 1. The results of different classifier for open MR images

	SVM (polynomial)	CART	SMO	SVM (linear)
Original	98.32(5.35)%	98.29(4.81)%	81.96(5.76)%	81.96(5.76)%
Segmentation	**98.41(5.11)%**	84.61(11.32)%	83.02(8.36)%	81.96(5.76)%

Note: The cell values are accuracy and standard deviations (in parentheses).

4.1.2. *Region hospital dataset experiment results.* This section uses the practically collected dataset from region hospital with 14687 brain MR images (normal 6579 and abnormal 8108). Normal images are collected from 25 patients and abnormal images are collected from 34 patients (cerebrovascular accident (CVA) 11 patients; brain tumor 13 patients; others 10 patients). The detail information of dataset is shown in Table 2.

Table 2. Region hospital dataset information

	Number of patients	Number of MR images	Filtered MR images
Normal	25	6579	511
CVA	11	2808	211
Brain tumor	13	3044	98
Others	10	2256	77

Table 3. The results of different classifier for region hospital dataset

	SVM-Polynomial (homogeneous)	SVM-Polynomial (inhomogeneous)	CART
Original with selection	73.69(1.22)%	73.76(0.99)%	**82.94(1.69)%**
Segmented without selection	**58.37(1.13)%**	58.07(0.91)%	56.44(1.48)%
Segmented with selection	77.32(0.72)%	77.68(0.91)%	**80.13(1.95)%**

Note: The cell values are accuracy and the standard deviations (in parentheses).

Table 4. The results of different classifier for 3 types of abnormal brain diseases

	Polynomial (homogeneous)	Polynomial (inhomogeneous)	CART
CVA	88.54(1.67)%	**89.19(1.77)%**	87.24(1.85)%
Brain tumor	88.22(1.28)%	88.65(0.62)%	**89.57(1.45)%**
Others	89.11(1.38)%	89.25(1.34)%	**89.85(1.31)%**

Note: The cell values are accuracy and the standard deviations (in parentheses).

In this section, 2/3 images are used for training, and 1/3 images are remained for testing. This paper repeats ten times experiments in different sampling, then utilizes SVM (polynomial, homogeneous/inhomogeneous) and CART as comparison methods. The SVM parameters setting range are $\mathcal{C} \in \{2^{-5}, 2^{-4}, \ldots, 2^{14}, 2^{15}\}$, $\gamma \in \{2^{-15}, 2^{-14}, \ldots, 2^{2}, 2^{3}\}$ and degree is 2. Further, we utilize the expert's mask to automatically select the brain MR images and reduce the dataset. After this step, 897 MR images (normal 511/abnormal 386; CVA 211/brain tumor 98/other 77) are selected. Then, we employ three different preprocess steps (original MR images with selection, segmented without selection, segmented with selection) in this experiment: (1) "Original with selection" denotes the original images after automatically selected by expert's mask; (2) "Segmented without selection" means the segmented MR images by proposed method and without selecting by expert's mask; and (3) "Segmented with selection" denotes the segmented images by proposed method and with automatically selecting by expert's mask. The experiment results are shown in Table 3. The three different types of abnormal brain MR images are used to re-validate the proposed method, and the result is shown in Table 4.

From Table 3, we can see that CART outperforms SVM in the experiment with filter process (original with selection, segmented with selection). However, SVM is superior to CART in the experiment without filter process (segmented without selection). Further, results generated by classification method with filter are better than results generated by classification method without filter. From Table 4, the results show that SVM generates better accuracy in CVA disease, and CART generates better accuracy in the brain tumor and other diseases.

4.2. **Findings.** From Tables 1, 3 and 4, the performance of different classification methods, there are some findings for this study as follows.

(1) The accuracy performance for different classification methods

In Tables 1, 3 and 4, SVM is superior to the listing methods in the Whole Brain Atlas dataset, but performances of SVM is weaker than CART method in region hospital dataset. In Table 4, we see that SVM can generate better accuracy in CVA. Therefore, SVM is fit to apply to classifying Alzheimer's disease (AD) and mild cognitive impairment (MCI) diseases, and is not suitable to classify hybrid dataset (assemble different kinds of brain diseases).

(2) Segmented MR image

From two experiments as Tables 1, 3 and 4, we can find that segmented MR images have better accuracy in SVM, and CART generates better accuracy in without segmented MR images. CART is not at all affected by the outliers, collinearities, heteroskedasticity, and distributional error structures, and the region hospital dataset has many noise. Therefore, the CART method is very fit to no segmented datasets, and SVM method is more appropriate to segmented datasets.

(3) Dataset quality

From the two experiments, we can see that the classification accuracy generated by different methods in Table 1 is better than the results in Tables 3 and 4. Table 1 uses Whole Brain Atlas dataset with selected clear MR images as experiment datasets, and the datasets would provide better classification criterion. On the other hand, the region hospital datasets are un-filtered MR images and real patient's situation. Though the accuracy of region hospital datasets is weaker than open dataset, the results of region hospital dataset have better reference values.

(4) Automatically selecting to reduce dataset

In Table 3, this paper utilizes Step 5 of proposed algorithm to effectively reduce dataset dimension. The shape filter remarkably provides good performances and automatically selecting MR images. Based on automatically selecting, the proposed algorithm can reduce time consuming and give better classification criterion.

5. **Conclusion.** This study has proposed a novel image processing method which combines automatic selecting MR images with semi-automatic segmentation and automatic classification. From experiments results, some academic contributions of this paper are as follows: (1) the proposed method could improve the normal and abnormal brain image classification accuracy; (2) the proposed automatically selected image method is a simple and feasible method, which can reduce time-consumption and cost; and (3) the methodology in this paper can provide some ideals for other researchers to create new image processing method. Further, the proposed method can improve the quality of medical care and there are two advantages: (1) for medical personnel: assisting medical staff to conduct the recognition of brain diseases and reduce their workload; and (2) for patients: to be appropriate diagnosed and cured for healthcare.

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