

# A Short Survey on MRI Brain Detection

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**Abstract**—Automated and accurate classification of MR brain images is of importance for the analysis. Recently researchers have proposed many different and innovative methods to improve upon this technology. This review focused on discussing the strength and limitations of earlier proposed classification techniques. Besides analyzing these literature, the paper also provides a critical evaluation of the surveyed literature which reveals new hotspots of research.

*Keywords*—magnetic resonance imaging; classification; computer-aided diagnosis

## I. INTRODUCTION

Magnetic resonance imaging (MRI) is capable of producing high quality images of the anatomical structures of the human body (especially the brain), while it is a low-risk, fast, non-invasive imaging technique. The rich information it provides is of great help for clinical diagnosis and biomedical research [1]. However, because of this huge information repository associated with MRIs, employing manual methods to interpret each image is tedious and time consuming, and it is of necessity to develop automated diagnosis tools to draw quicker and easier inferences from the MRI images. These automated tools can benefit the medical personnel in diagnosis, prognosis, pre-surgical and postsurgical procedures, etc. [2].

Sophisticated signal/image processing techniques and some computational intelligent techniques are applied to develop diagnostic tools. In one possible methodology, the problem of automatic classification of normal/pathological subjects, based on brain MRIs, can be configured as a three-stage problem: 1) feature extraction; 2) feature reduction; 3) classification [3].

The main contribution of this study is to review the most recent classification algorithms and their state-of-the-art. We summarized the advantages and disadvantages of the reviewed algorithms in tables to provide a structured vision aspects involved in these algorithms.

This paper is organized as follows: Section 2 presents the recent classification algorithms and their experiment results. Section 3 discusses the limitations of these methods, while the conclusion and future work are presented in Section 4.

## II. METHODS AND RESULTS

Chaplot, Patnaik, and Jagannathan [4] used the approximation coefficients obtained by discrete wavelet transform (DWT), and employed the self-organizing map (SOM) neural network and support vector machine (SVM). The classification percentage of more than 94% in case of self-organizing maps and 98% in case of support vector machine.

However, the number of their extracted features reached as high as 4761 which increases the computational time. Meanwhile, their method was only applied to axial T2-weighted images at a particular depth inside the brain, and the dataset in their experiment is too small only containing 52 images.

Maitra and Chatterjee [3] employed the Slantlet transform, which is an improved version of DWT for feature extraction. Their feature vector of each image is created by considering the magnitudes of Slantlet transform outputs corresponding to six spatial positions chosen according to a specific logic. Then, they used the common back-propagation neural network (BPNN).

The system they developed could achieve an excellent classification accuracy of 100%, while the number of the features for the classifier input is only six, which obviously lightened computational burden. However, their method was only tested on AD.

El-Dahshan, Hosny, and Salem [5] extracted the approximation and detail coefficients of 3-level DWT, reduced the coefficients by principal component analysis (PCA), and used feed-forward back-propagation artificial neural network (FP-ANN) and K-nearest neighbor (KNN) classifiers.

The FP-ANN and KNN achieved accuracy of 97% and 98%, respectively. However, whenever the image database increased, a fresh training is required for the proposed system before it works again, which is inconvenient in practical use, and the classification performance can be improved.

Zhang, Wu, and Wang [6] proposed using DWT for feature extraction, PCA for feature reduction, and FNN with scaled chaotic artificial bee colony (SCABC) as classifier. Based on it, Zhang, Dong, Wu, and Wang [7] suggested to replace SCABC with scaled conjugate gradient (SCG) method. Both algorithms achieved 100% accuracy, and the computation time per image is only 0.0451 s. However, the dataset is too small only containing 66 images, and the requirement for

computation time could be decreased if they used advanced wavelet transforms such as lift-up wavelet.

Zhang and Wu[8] proposed to use kernel SVM as classification method, and found the GRB kernel achieved the highest accuracy of 99.38%. The prediction time of a 256x256 image was only 0.0448s.

Future scope of their paper is that, they'll test novel kernels to increase the classification accuracy. Meanwhile, multi-classification can also be explored, which focuses on specific disorders utilizing brain MRI.

Saritha, Joseph, and Mathew[9] proposed a novel feature of wavelet-entropy (WE), employed spider-web-plot (SWP) to further reduce features, and used the probabilistic neural network (PNN). The classification accuracy was found to be 100% on a 75-image dataset with four diseases.

The limitation of their work is that once there is an increase in image database, fresh training is required. The size of dataset was small and the number of categories of diseases is too little. The efficiency of the developed system could be improved, since Zhang, Dong, Ji, and Wang [10] suggested that removing spider-web-plot yielded the same classification performance later.

Das, Chowdhury, and Kundu[2] proposed to use a hybrid method for classification. First they employed Ripplet transform (RT) to extract features from MRIs. And then the feature of Magnetic Resonance Image has been reduced by using Principal Component Analysis (PCA). Afterwards, they developed a classifier based on least square SVM (LS-SVM). Five-fold cross-validation was utilized to avoid overfitting.

With this combination, they not only achieved higher feature reduction, but also acquired superior performance, which showed high classification accuracy of 99.39% over a 255-image dataset. However, the time requirement for feature extraction through RT is slightly greater than DWT.

Zhang, Wang, Ji, and Dong[11] suggested a hybrid system, integrating DWT, PCA, PSO, KSVM, and CV, to identify normal MR brains from abnormal MR brains. The proposed method first employed digital wavelet transform to extract features, and then used principal component analysis (PCA) to reduce the feature space. Afterwards, they constructed a kernel support vector machine (KSVM) with RBF kernel, using particle swarm optimization (PSO) to optimize the parameters  $C$  and  $\sigma$ . Fivefold cross-validation was utilized to avoid overfitting.

The classification result on a 90-image database achieved 97.11% accuracy, which shows that the PSO is more effective to find the optimal values than random selection method. The classification capability of KSVM can be improved by integrating PSO. However, advanced wavelet transforms, such as the lift-up wavelet, can be helpful to accelerate the computation time.

Kalbkhani, Shayesteh, and Zali-Vargahan[12] modelled the detail coefficients of 2-level DWT by generalized autoregressive conditional heteroscedasticity (GARCH) statistical model, and the parameters of GARCH model are considered as the primary feature vector. Their classifier was chosen as KNN and SVM models.

KNN and SVM classifiers achieved 97.62% and 98.21% accuracy for the eight-class classification, respectively.

Also, for two-class classification both classifiers achieve 100% accuracy. Considering that the problem is multi-classification, and the number of features is relatively low, the result is outstanding. However, the feature extraction process of the system requires relatively more time.

Padma and Sukanesh[13] used combined wavelet statistical texture features, to segment and classify AD benign and malignant tumor slices. First, Two dimensional discrete wavelet decomposition is performed on the tumor image to remove the noise. Then a total of 17 features are extracted and six features are selected using Student's t test. Finally, the reduced optimal features are used to model and train the probabilistic neural network classifier and the classification accuracy is evaluated using k fold cross validation method.

Their classification model achieved 97.39 % classification accuracy based on SVM tumor segmentation and 2D-DWT preprocessing. However, the limitation of this method is that it needs new training for the PNN classifier whenever there is change in the slice data set and it can't be applied to brain imaging techniques but CT.

El-Dahshan, Mohsen, Revett, and Salem [14] used the feedback pulse-coupled neural network for image segmentation, the DWT for features extraction, the PCA for reducing the dimensionality of the wavelet coefficients, and the FBPNN to classify inputs into normal or abnormal.

The accuracy achieved 99% on a 101-image dataset. However, if they extract more efficient features and increase the training dataset, the classification can be more accurate.

Zhang, Wang, and Dong[15] presented a diagnosis method to distinguish Alzheimer's disease (AD) and mild cognitive impairment (MCI) from normal controls, based on structural MR images by kernel SVM Decision Tree. A 5-fold cross validation showed their method yielded 80% accuracy for these three classes, and the computation time to predict a new patient is only 0.022 s.

The limitation of their method is that the meanings of weights/biases of the kSVM-DT mean can't be understood by ordinary technicians, since the classifier establishes machine-oriented rules instead of human-oriented rules. Another limitation is that the classification accuracy needs to be improved. However, structural MRI may not cover the sufficient information containing the cause of AD.

Zhou, et al. [16] used wavelet-entropy as the feature space, then they employed a Naive Bayes classifier (NBC) classification method. Their results over 64 images showed that the sensitivity of the classifier is 94.50%, the specificity 91.70%, the overall accuracy 92.60%.

However, ordinary technicians have difficulty interpreting the entropy values or the weights/biases of NBC. Meanwhile, multi-disease classification was the future research direction, since their classifier can only perform two-class classification. Finally, the small dataset may introduce error to the reported classification accuracy.

Zhang, Dong, Wang, Ji, and Yang[17] used discrete wavelet packet transform (DWPT), and harnessed Tsallis entropy to obtain features from DWPT coefficients. Then,

they used a generalized eigenvalue proximal SVM (GEPSVM) with RBF kernel.

This combination yielded superior performance, achieving 99.61% accuracy. However, the limitation was that the classifier was machine-oriented instead of human-oriented. Although machine-oriented classifiers are better in classification performance than human-oriented classifiers, it is difficult for technicians to understand or interpret the meanings of weights/biases of the classifier, which is inconvenient in practical use. And the computation of DWPT is relatively time-consuming.

Yang, et al.[18] selected wavelet-energy as the features, and introduced biogeography-based optimization (BBO) to train the SVM. Their method reached 97.78% accuracy on 90 T2-weighted MR brain images.

Future scope of their paper is that, they'll replace wavelet-energy with more efficient feature descriptors, such as scale-invariant features and employ advanced pattern recognition techniques, such as deep learning and RBFNN. Multiple slices can be employed in order to improve the classification performance. They'll also test whether higher level can lead to better classification performance by increasing the decomposition level of 2D-DWT.

### III. DISCUSSION

In this review, we gave an overview of the state of the art in the MRI-based medical image classification methods. It can be easily observed that the method is becoming mature. The characteristics of different methods are summarized in Table 1.

**TABLE 1:** Comparison of Different Brain Image Classification Methods

No	Author	Year	Method used	Limitation	Accuracy
1	Chaplot, Patnaik, and Jagannathan	2006	Discrete wavelet transform (DWT), self-organizing maps (SOM) and support vector machine (SVM).	The number of the features is too high, and their method was only applied to axial T2-weighted images.	94% for SOM and 98% for SVM
2	Maitra and Chatterjee	2006	Slantlet transform (ST) and back propagation neural network (BPNN).	Their method was only tested on AD.	100%
3	El-Dahshan, Hosny, and Salem	2010	3-level DWT, principle component analysis (PCA), feed-forward back-propagation artificial neural network (FP-ANN) and K-nearest neighbor (k-NN)	It requires fresh training each time whenever there is an increase in image database.	97% for FP-ANN and 98% for k-NN
4	Zhang, Wu, and Wang	2011	Discrete wavelet transform (DWT), principle component analysis (PCA) and FNN with scaled chaotic artificial bee colony (SCABC).	Their method was only applied to T2-weighted images.	100%
5	Zhang, Wu, and Wang	2011	Discrete wavelet transform (DWT), principle component analysis (PCA) and back propagation neural network (BPNN) with conjugate gradient (SCG).	The dataset only contains 66 images.	100%
6	Zhang and Wu	2012	Discrete wavelet transform (DWT), principle component analysis (PCA) and kernel support vector machine (KSVM) with GRB kernel.	The computation time could be accelerated by using advanced wavelet transforms such as the lift-up wavelet.	99.38%
7	Saritha, Joseph, and Mathew	2013	Wavelet entropy based spider web plots and probabilistic neural network.	The size of dataset was small and the number of categories of diseases is too little. The same classification performance can be yielded if the spider-web-plot is removed.	100%
8	Das, Chowdhury, and Kundu	2013	Ripplet transform (RT), PCA, least square SVM (LS-SVM), and the 5x5 CV	The time requirement for feature extraction through RT is slightly greater than DWT.	99.39%
9	Zhang, Wang, Ji, and Dong	2013	Discrete wavelet transform (DWT), PCA, particle swarm optimization (PSO), and KSVM with RBF kernel.	The computation time could be accelerated by using advanced wavelet transforms such as the lift-up wavelet.	97.11%
10	Kalbkhani, Shayesteh, and Zali-Vargahan	2013	Discrete wavelet transform (DWT), generalized autoregressive conditional heteroscedasticity (GARCH), K nearest neighbor (KNN) and support vector machine (SVM)	The feature extraction process requires relatively more time.	97.62% for k-NN and 98.21% for SVM
11	Padma and Sukanesh	2014	Combined wavelet statistical texture features, discrete wavelet transform (DWT), support vector machine (SVM), and Probabilistic Neural Network (PNN)	It needs new training for the PNN classifier whenever there is change in the slice data set and the method can be applied to brain CT images only.	97.39%
12	El-Dahshan, Mohsen, Revett, and Salem	2014	Discrete wavelet transform (DWT), PCA, and feedback pulse-coupled neural network (FBPNN).	The classification accuracy can be improved by extracting more efficient features and increasing the training dataset.	99%
13	Zhang, Wang, and Dong	2014	PCA, and kernel SVM Decision Tree.	The classifier establishes machine-oriented rules not human-oriented rules.	80%
14	Zhou, et al.	2015	2D-discrete wavelet transform, wavelet-entropy, and Naive Bayes classifier.	It is difficult to interpret the entropy values or the weights/biases of NBC.	92.60%
15	Zhang, Wang, Dong, Ji, and Yang	2015	Discrete wavelet packet transform, harnessed Tsallis entropy, and generalized eigenvalue proximal SVM (GEPSVM) with RBF kernel.	The classifier was machine-oriented not human-oriented. And DWPT takes the most time during either the offline learning stage or online prediction stage.	100%, 100%, and 99.53% on Dataset-66, Dataset-160, and Dataset-255, respectively
16	Yang, et al.	2015	Wavelet-Energy, SVM, and biogeography-based optimization (BBO).	Wavelet-energy is less efficient than some other feature descriptors, such as scale-invariant features.	97.78%

#### IV. CONCLUSION

In this paper we have accomplished a short survey of recent detection techniques for MRI brain image. After the analysis of well-known techniques it is clearly shown that various methods which can classify MR brain images efficiently and provide accurate result. As the classification of MR brain images still remains an open problem, there are more novel classification techniques which perform more efficiently and more accurately, such as HPA method [19], 3D-DWT method [20], and eigenbrain [21], which will be included in our future research.

From this survey we find that most of the latest existing methods are to develop two-class classifier, while the development of multi-class classifier is still at an initial stage. We believe this will be a hot spot in a foreseeable future.

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