ANALYSIS OF DIFFERENT WAVELETS FOR BRAIN IMAGE CLASSIFICATION USING SUPPORT VECTOR MACHINE

Mohankumar S,
Department of Computer Science and Engineering,
New Horizon College of Engineering,
Bangalore, India
drsmohankumar@gmail.com

Abstract: Automated classification of medical images with high accuracy is crucial when dealing with human life. In this paper, Discrete Wavelet Transform (DWT) based classification of Magnetic Resonance Images (MRI) of the brain is presented. The given input images are de-noised using a median filter in the preprocessing stage. Then, the de-noised images are given as inputs to the wavelet transform. The wavelet transform is used for feature extraction purpose. Most transformation techniques produce coefficient values with their dimension same as the original image. Further processing of the coefficient values must be applied to extract the image feature vectors. Predefined families of wavelets such as Daubechies (db8), Symlets (sym8) and Biorthogonal (bio3.7) are used. From that energy information's are extracted and provided as input to the recognition or classification stage. Finally, the brain images are classified by Support Vector Machine (SVM) classifier whether it is normal or abnormal. Results show that db8 filter provides higher accuracy than other wavelets.

Keywords: Brain Tumor, DWT, Db8, Sym8, bio3.7, SVM.

I. INTRODUCTION

MRI is a non-invasive procedure to detect abnormalities in the brain. Many MRI image classification procedures are available recently. Some of the procedures are outlined here. A hybrid approach for the classification and detection of the brain tumour through MRI is explained in [1]. The first stage is preprocessing in which skull detection and denoising are done. The next phase deals Gray Level Co-Occurrence Matrix (GLCM) as features of MR brain images. It uses multilayer perceptron kernel in Least Squares Support Vector Machine (LS-SVM) to classify the images.

A study about brain tumour diagnosis is presented in [2] by MRI feature analysis. Discrete Cosine Transform (DCT) and DWT techniques are studied independently and also combined. At first, the removal of noise and sharpening of MRI image are taken place. Then, the aforementioned techniques DWT and DCT are used for feature extraction. Finally, the abnormality of given MRI brain is accessed using Probabilistic Neural Network (PNN) which uses Radial Basis Function (RBF).

Sparse coding and dictionary learning for brain tumour classification are described in [3]. The sparse coding classification and individual dictionary learning (per-class) are employed by k-means singular value decomposition. Brain tumour classification using Artificial Neural Networks (ANN) design is discussed in [4]. Back Propagation Neural Network (BPNN) and RBF networks are used to classify brain MRI images. Statistical features are used as features.

SVM and meta-heuristic methods for brain tumour classification are explained in [5]. The spatial gray level dependence matrix and DWT based features are mainly used. Simulated annealing is employed to select the features so that the dimension of the feature set is reduced. The SVM parameters are optimized using Genetic Algorithm (GA). Two Matrix Factorization (MF) methods such as Non-negative MF (NMF) and Local NMF (LNMF) for brain tumour classification are presented in [6]. Firstly, NMF and LNMF are applied to metabolite profiles to extract features. These features are trained by Linear Discriminant Analysis (LDA) and SVM for brain tumour classification.

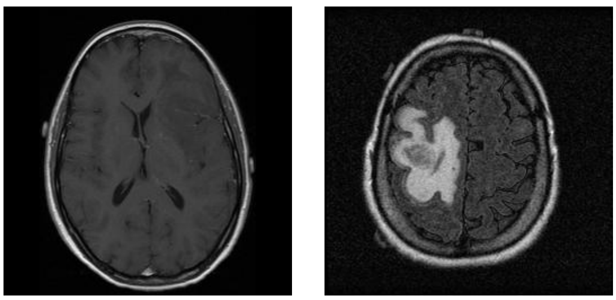
Clinical based features for brain tumour classification using Bayesian model is discussed in [7]. First, clinical based features are analyzed. Then, a Bayesian model is used to fuse multiple individual scores obtained from the MRI image sequence and its pathological indictor. Multiclass brain tumour classification using GA and SVM is described in [8]. It uses intensity and texture features of tumours as input. The most informative features are selected using GA and the selected features are trained by SVM for the classification. DCT and PNN for brain tumour classification are explained in [9]. Decision making is performed in two steps. First, features are extracted by DCT and feature dimension is reduced by dimensionality reduction. The second step uses PNN as a classifier.

Brain tumour identification and classification based on K-Nearest Neighbor (kNN) is presented in [10]. kNN algorithm is based on majority voting approach. Manhattan metric is applied to calculate the distance between the features. kNN and Linear SVM for brain tumour classification is discussed in [11]. At first, a Gaussian filter is applied for noise reduction. Then, intensity and texture based features are extracted. The dimensionality of feature space is reduced by principal component analysis. The classification stage uses two classifiers; Linear SVM and kNN. Vivo MR Spectroscopy (MRS) images are analyzed for brain tumour classification using LDA and SVM in [12]. The quantification of MRS is done by LCModel. It uses RBF kernel in LS-SVM for classification.

II. METHODS AND MATERIALS

A. Preprocessing

Preprocessing is the essential step in any machine learning techniques. The median filter is used to denoise an image from the given MRI brain image. Then the de-noised images are given as input to the next stage to extract the features using DWT technique. Figure 1 shows the MRI brain normal image and MRI brain abnormal image respectively.



(a) ***(b)***

Fig. 1(a) MRI brain normal image (b) MRI brain abnormal image

B. Feature Extraction using DWT

After preprocessing, the steps for feature extraction include DWT decomposition. The coefficients of DWT of MRI brain images are computed. Db8, Sym8, and bio3.7 are the wavelet filters which are used for extracting energy features. Along with spatial information, frequency information of given input data is captured by DWT. These information's are obtained by decomposing the given input data by DWT via the low pass and high pass filtering. The former filtering produces coarse approximation, and the later filtering technique gives detail information's. The multiresolution of the given input data is obtained by giving the coarse approximation as input to DWT process until it reaches the required level of decomposition.

C. Classification

The extracted features are applied to the SVM to determine the category of MRI. It is one of the state-of-art learning approaches used for classification. Many studies show its computation advantages with better accuracy over traditional learning approaches. It can perform binary and multi-class classification tasks. However, binary SVM is used in this study as the system classifies the given input as normal/abnormal. RBF Kernel function is used in this system. Finally, properly extracted features are classified by the SVM classifier.

III. RESULTS AND DISCUSSION

The system is tested on a clinical MRI data set. Total number of MRI brain images in the dataset is 100. The brain images with lesions are categorized into abnormal images and without lesions are categorized into normal images by experts. Each category contains 50 MRI brain images. Selected images are given as input to the preprocessing stage to denoise an image. Next features are extracted using DWT coefficients. Finally, classification is achieved by SVM classifier whether it is a normal or abnormal image. Table 1 shows the overall accuracy of the method using DWT features and SVM classifier.

TABLE 1 Performance of different wavelet filters in MRI brain image classification

DWT decomposition level	Normal			Abnormal		
	Db8	**Sym8**	**bio3.7**	**Db8**	**Sym8**	**bio3.7**
1	76	70	68	78	72	70
2	82	80	76	84	82	76
3	88	84	82	89	84	80
4	92	88	88	95	90	88
5	90	84	82	90	82	78

IV. CONCLUSION

In this study, three wavelet filters are analyzed for MRI brain image classification. It classifies the MRI brain images into normal/abnormal by SVM classifier which uses the energy features of db8, sym8, and bior3.7. Among the filters, db8 provides better classification accuracy of 92% for normal and 95% for abnormal image classification. In future, other multi resolution analysis such as curvelet, contourlet, and Shearlet could be analyzed for MRI brain image classification.

REFERENCES

[1]. G.B. Praveen, and A. Agrawal, "Hybrid approach for brain tumor detection and classification in magnetic resonance images", IEEE Communication, Control and Intelligent Systems, 2015, pp. 162-166.

[2]. G. Shobana, and R. Balakrishnan, "Brain tumor diagnosis from MRI feature analysis-A comparative study", IEEE International Conference on Innovations in Information, Embedded and Communication Systems, 2015, pp. 1-4.

[3]. S.D.S. Al-Shaikhli, M.Y. Yang, and B. Rosenhahn, "Brain tumor classification using sparse coding and dictionary learning", IEEE International Conference on Image Processing, 2014, pp. 2774-2778.

[4]. S.N. Deepa, and B.A. Devi, "Artificial neural networks design for classification of brain tumour", IEEE International Conference on Computer Communication and Informatics, 2012, pp. 1-6.

[5]. A. Kharrat, M.B. Halima, and M.B. Ayed, "MRI brain tumor classification using support vector machines and meta-heuristic method", IEEE 15th International Conference on Intelligent Systems Design and Applications, 2015, pp. 446-451.

[6]. D. Lu, Y. Sun, and S. Wan, "Brain tumor classification using non-negative and local non-negative matrix factorization", IEEE International Conference on Signal Processing, Communication and Computing, 2013, pp. 1-4.

[7]. T. Martinez-Cortes, M.A. Fernandez-Torres, A. Jimenez-Moreno, I. Gonzalez-Diaz, F. Diaz-de-Maria, J.A. Guzman-De-Villoria, and P. Fernandez, "A Bayesian model for brain tumor classification using clinical-based features", IEEE International Conference on Image Processing, 2014, pp. 2779-2783.

[8]. J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C.K. Ahuja, "Multiclass brain tumor classification using GA-SVM", IEEE Developments in E-systems Engineering, 2011, pp. 182-187.

[9]. D. Sridhar, and I.M. Krishna, "Brain tumor classification using discrete cosine transform and probabilistic neural network", IEEE International Conference on Signal Processing Image Processing & Pattern Recognition, 2013, pp. 92-96.

[10]. K. Sudharani, T.C. Sarma, and K.S. Rasad, "Intelligent Brain Tumor lesion classification and identification from MRI images using k-NN technique", IEEE International Conference on Control, Instrumentation, Communication and Computational Technologies, 2015, pp. 777-780.

[11]. G.K. Sundararaj, and V. Balamurugan, "Robust classification of primary brain tumor in Computer Tomography images using K-NN and linear SVM", IEEE International Conference on Contemporary Computing and Informatics, 2014, pp. 1315-1319.

[12]. L. Wang, S. Wan, Y. Sun, B. Zhang, and X. Zhang, "Automatic Classification of Brain Tumor by in Vivo MRS Data based on LDA and SVM", IEEE Seventh International Conference on Measuring Technology and Mechatronics Automation, 2015, pp. 213-216.