Review Article Bioinformatics

International Journal of Pharma and Bio Sciences

ISSN
0975-6299

ROLE OF CLASSIFICATION ALGORITHMS ON BRAIN MRI DATA

MUKULIKA PANDA[1], SASHIKALA MISHRA[2], KAILASH SHAW[3],DEBAHUTI MISHRA[4]

1,4 Institute of Technical Education and Research, Siksha 'O' Anusandhan University ,Bhubaneswar
2 Department of Computer Engineering, International Institute of Information Technology, Pune,*
3, Department of Computer Engineering, D Y Patil College of Engineering, Akurdi, Pune

ABSTRACT

Image classification is an important problem of computer vision. In the world of medical science everyday doctors are encountered with various types of image related problem. Pattern classification is a solution to categorize the images. In this paper we have considered the medical dataset like Brain Tumor. To select the appropriate features PCA has been used in the paper. The Otsu's method is used to find a segmented image of brain MRI data where as for classification SVM with various kernel functions has been implemented and the result has been established in the manuscript.

KEYWORDS: Image, Classification, PCA, Kernel Functions, SVM

SASHIKALA MISHRA
Department of Computer Engineering, International Institute of Information Technology, Pune

INTRODUCTION

Brain is the vital part of the human body. Brain tumour is a very serious disease occurs because of uncontrolled growth of cells in the brain. There are different type of tumours occur in the brain, such as benign and malignant. Benign is a non-cancerous tumour, grow slow while malignant tumour is a cancerous tumour, grow fast and causes serious harm to the brain which causes death[1]Magnetic resonance imaging (MRI) is an imaging technique that provides high pixel images of the internal structures of the human body, especially in the brain, and provides various information for medical diagnosis and biomedical research[2-6]. The goal of Image segmentation is to divide an image into its required regions or objects like separation of foreground from background. It is one of the toughest challenges in Image processing and computer vision[7] as it serves as a fundamental step to object recognition, image retrieval, image understanding. A several researches found for image segmentation such as threshold methods, Otsu's method, graph based methods, active contour method, region based methods, edge detection methods, clustering methods, and other hybrid method. A histogram method doesn't work well for images whose histograms are nearly unimodal. Edge based method are not suitable well for complex and noise data as it focus on detecting pixel on the edge of the object. In region growing method over segmentation and under segmentation are critical issues. Graph based methods are high computational complexity. Due to the efficiency and simplicity[8]of Otsu's Method it's mostly used. Here in this paper, for feature extraction PCA is used. And also for better classification we KSVM (Kernel Support Vector Machines) have been used. SVMs are [9] techniques suitable for binary classification task. In this paper we define the KSVM having four of its kernel functions namely RBF accuracy, Linear accuracy, Polygonal accuracy, Quadratic Accuracy. There are so many features like Mean, Standard deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy, Homogeneity etc.

LITERATURE SURVEY

Depending on the single scale and multiscale saliency,Xuefei Bai *et al*.[7] has introduced context aware saliency to detect the image regions. Lately,Y. Zhang*et.al*[9] has implemented GRB kernel SVM and found out 99.38% classification accuracy on the 160 MR images. M Vaidyanathan*etal.*[11]explainedmany supervised methods to overcome the multi- and hyper spectral data classification problem.AshimaAnand*et.al* has implemented threshold based and region growing techniques for detecting tumours from normal tissues based on their image intensity[12].Author B. Scholkopf *et al.* has implemented Support Vector(SV) machine technique for identifying the tumour region accurately in the brain via MRI images and classification also has been performed on a brain tumour image for identifying the benigntumor or malignant tumor[15]. It gives maximum classification accuracy and used in various practical applications. Qurat-ul Ain *et al*. (2010) has implemented a robust system for brain tumour diagnosis and for brain tumour region extraction. Using Naïve Bayes classifier, the tumor from the brain MR images has diagnosed and then K-means clustering and boundary detection techniques has been implemented to locate the brain tumor region. Here 99% accuracy for diagnosis and the accurate region of tumor was found out properly. Gustavo camps-Valls*et.al.*[20]has proposed that Radial Basis Function Neural Network(RBFNN)gives good efficiency with less number of labelled samples. Dipthy Murthy on 2014 has implemented some thresholding and morphological algorithm on the Brain MRI data extracted some of the feature of the tumor to classify them well. Vishal B.Padole on 2012 has been found that Mean Shift Algorithm segment the proper area of the tumor for further classification. The section 3 describes the formal steps to detect the brain tumor, section 4 deals with the methodologies used for the classification of the brain MRI data, section 5 deals with the importance of the kernel functions, where section 6 deals with the experimental result and analysis and the paper ends with the conclusion section.

GENERALIZED BRAIN TUMOR DETECTION SYSTEM

The structure of any brain tumor detection system mainly consists of five sections as following:

- Image Acquisition: Acquisition of the image is the first step of image processing. Brain MRI images can be acquired from publicly available databases.
- Image Pre-processing: In this step, we segment the required image into its constituent regions. The main goal of the image pre-processing is to improve the image data and reduce the effect of noise.
- Feature Reduction: Excessive features increases computation times and storage memory. They sometimes make classification more complicated, which is called the curse of dimensionality. Here by using PCA we have reduced the number of features.
- Classification: it's the categorization process by which we assign the class level to the data and further test if any new data comes to the assigned class level of data.
- Accuracy assessment: By applying different methods/algorithms we can find the accuracy of the different class of data.

METHODS

In this work several algorithms has been used like, Otsu's Method (for segmentation), PCA (for feature extraction), and KSVM (for classification) to classify the data properly. Otsu's Method reduces a grey level image to a binary image. The algorithm determines that which pixel goes under foreground and which pixel goes under background. An image havingmuch grey level is converted into fewer grey levelimages and comparison is done on each pixel intensity with a reference value T(Threshold). If input image $f(x,y)$ and Binary version is $g(x, y)$ then, $g(x, y)=1$ if $f(x,y)>= T$ or 0 otherwise.To reduce the number of unwanted features sets from data set, PCA has been used in the paper.

ROLE OF KERNEL FUNCTIONS IN SVM

To select a proper classification algorithm for image is really a tedious task. The linear SVM classifier takes an input data from feature set and classify into two possible classes. That's why the nonlinear SVM works in a good way on high dimensional feature sets. To increase the margin of the classification, kernel functions are used. There are many kernels used in support vector machine such as radial basis function (RBF), linear, polynomial etc.[9]Kernel SVM gives the clear understanding of the classification and very easy to use in practical image processing. In this paper some of its methods like RBF, linear, and polygonal are used to find the segmented image. Several features of the data set have been considered like Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy, Homogeneity etc. for the classification methods.

EXPERIMENTAL SETUP AND RESULT ANALYSIS

This Brain tumour dataset was collected from the University Medical Centre, Institute of Oncology, and Ljubljana, Yugoslavia[16]. This data consists of two types of tumour class for i.e. Benign and Malignant.The Ostu's method is used in MRI data for segmentation the segmented data used SVM as learning algorithms with 4 kernel functions.

SOME SEGMENTED MRI DATA OF BENIGN CLASS

Total 11 images has been considered from which only three has shown in the figure

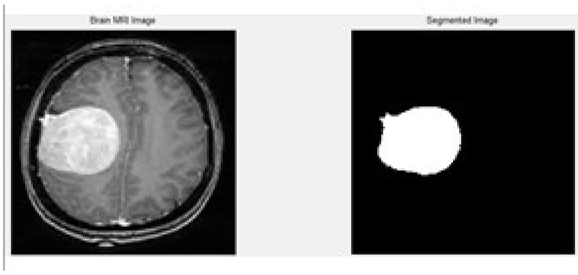

Figure 1
Segmented Image of Benign Data

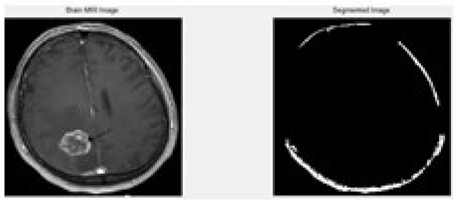

Figure 2
Segmented Image of Benign Data

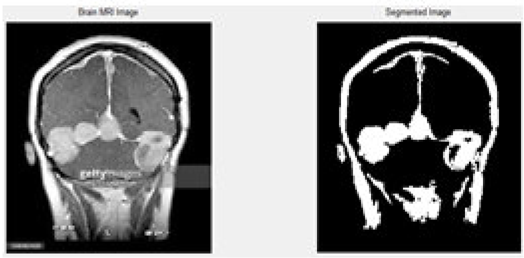

Figure 3
Segmented Image of Benign Data

SEGMENTED MRI DATA OF MALINGNANT CLASS

Similarly this class of the cancer data consists of 12 images from which some are shown below.

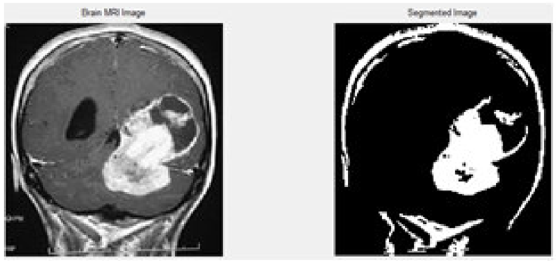

Figure 1
Segmented Image of Malingnant Data

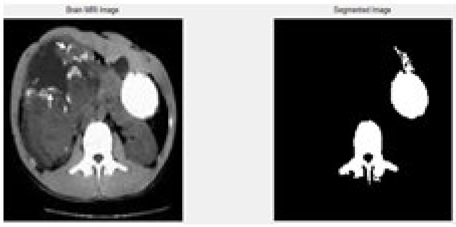

Figure 2
Segmented Image of Malingnant Data

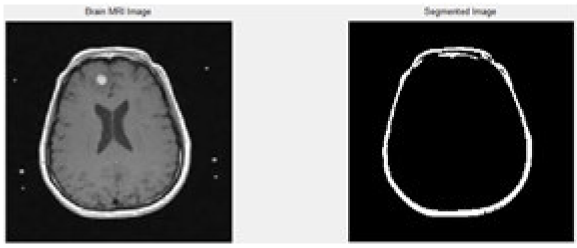

Figure 3
Segmented Image of Malingnant Data

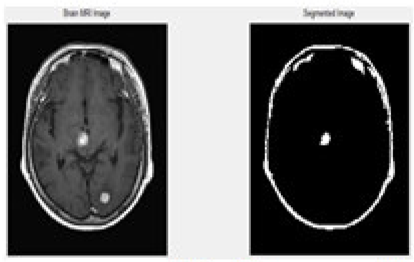

Figure 4
Segmented Image of Malingnant Data

After segmentation of the image data, it used for classification using SVM. The SVM used kernel functions like RBF, Linear, Polynomial and Quadratic to achieve the accuracy. 11 images from class1 and 12 images are from class 2 tested to find the accuracy of the algorithm. Table 1 and Table 2 represents the accuracy level according to the image class

Table 1
Accuracy observed using different kernel functions for benign data set

Benign tumour image data	RBF accuracy in %	Linear accuracy in %	Polynomial accuracy in %	Quadratic accuracy in %	Mean
Image1	90.91	72.72	81.81	81.81	81.81
Image2	81.82	72.72	90.90	81.81	81.81
Image3	81.81	81.81	81.81	90.90	84.08
Image4	81.81	72.72	100	81.81	84.08
Image5	90.90	72.72	81.81	90.91	84.08
Image6	90.90	72.72	90.90	81.81	84.08
Image7	90.90	72.72	90.90	81.81	84.08
Image8	81.81	81.81	90.90	90.90	86.35
Image9	81.81	72.72	81.81	100	84.08
Image10	81.81	72.72	90.90	90.90	84.08
Image11	90.90	72.72	81.81	81.81	81.81

Table 2
Accuracy observed using different kernel functions for Malignant data set

Malignant Image Type of data	RBF accuracy in %	Linear accuracy in %	Polynomial accuracy in %	Quadratic accuracy in %	Mean
Image1	81.81	72.72	90.90	81.81	81.81
Image2	81.81	72.72	81.81	81.81	79.53
Image3	81.81	72.72	81.81	81.81	79.53
Image4	81.81	72.72	90.90	81.81	81.81
Image5	90.90	72.72	90.90	90.90	86.35
Image6	90.90	72.72	90.90	81.81	84.08
Image7	90.90	72.72	90.90	81.81	84.08
Image8	81.81	72.72	81.81	100	84.08
Image9	81.81	81.81	90.90	90.90	86.36
Image10	81.81	72.72	81.81	100	84.08
Image11	81.81	72.72	81.81	90.90	81.81
Image12	81.81	72.72	81.81	81.81	79.53

CONCLUSION

In this paper, Otsu's segmentation works really well for Brain MRI data to segment and PCA performed better results for feature reduction. In particular, we have analysed and compared four of the kernel functions of SVM with a standard brain MRI data. In future we can use others feature reduction method and can compare and find the accuracy. The researcher can also use various hybridized learning algorithms with variety of dataset

CONFLICT OF INTEREST

Conflict of interest declared none.

REFERENCES

1. Ghotekar, Bhavana B. and K. J. Mahajan. MRI Brain image Segmentation and Classification: A Review. International Research Journal of Engineering and Technology (IRJET). 20163:1170-6.
2. Zhang, Yudong, Leann Wu, Shuihua Wang. Magnetic resonance brain image classification by an improved artificial bee colony algorithm. Progress In Electromagnetics Research. 2011;65-79.
3. Mohsin, S. A., N. M. Sheikh, and U. Saeed. MRI induced heating of deep brain stimulation. leads: Effect of the air-tissue interface,Progress In Electromagnetics Research. 2008;83:81-91.
4. Golestanirad, L., A. P. Izquierdo, S. J. Graham, J. R. Mosig, and C. Pollo. Effect of realistic modeling of deep brain stimulationon the prediction of volume of activated tissue. Progress In Electromagnetics Research. 2012;126:1-6.
5. Mohsin, S. A.Concentration of the specific absorption ratearound deep brain stimulation electrodes during MRI. Progress In Electromagnetics Research. 2011;121:469-84
6. Oikonomou, A., I. S. Karanasiou and N. K. UzunogluPhased-array near field radiometry for brain intracranial applications. Progress In Electromagnetics Research.2010;109:345-60
7. XuefeiBai, Wenjiann WangSaliency. SVM: An automatic approach for image segmentation. Neurocomputing.2014;243-4
8. Miss Hetal J. Vala, Prof. AsthaBaxi.A Review on Otsu Image Segmentation Algorithm. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 2013;387-9.
9. Zhang, Yudong, Lenan Wu. An MR brain images classifier via principal component analysis and kernel support vector machine. Progress In Electromagnetics Research, 2012;130:369-88
10. S.Haykin, Simon. Neural Network:A comprehensive foundation. Neural Networks.2004.
11. Vaidyanathan M Clarke LP, Velthuizen RP, Phuphanich S, Bensaid AM, Hall LO, Bezdek JC, Greenberg H, Trotti A, Silbiger M. ,.Comparison of supervised MRI segmentation methods for tumor volume determination during therapy. Magnetic resonance imaging.1995;13(5):719-28.

12. Ashima Anand, HarpreetKaur. Survey on Segmentation of Brain Tumor. A Review of Literature. International Journal of Advanced Research in Computer and Communication Engineering. 2016;79-82
13. Tamije, P., V. Palanisamy, and T. Purusothaman. Performance Analysis of Clustering Algorithms in Brain Tumor Detection of MR Images. European Journal of Scientific Research.2011;62:321-30.
14. Mrs.Bharati R. Jipkate, Dr. Mrs. V. V. Gohokar. A Comparative Analysis of Fuzzy C-means Clustering and K-means Clustering Algorithms. International Journal of computational Engineering Research. 2012;2:737-9
15. B Scholkopf, KK Sung, CJC Burges . Comparing support vector machines with Gaussian kernels to radial basis function classifiers. Signal Processing IEEE Transactions. 1997;45:2758-65
16. URL:https://archive.ics.uci.edu/ml/machine-learning-databases/primary-tumor/.
17. G. Giacinto L. Bruzzone. Combination of neural and statistical algorithms for supervised classification of remote-sensing images Pattern Recognition. 2000;21:399:405
18. Despotović, Ivana, Bart Goossens, Wilfried Philips. MRI segmentation of the human brain: challenges, methods, and applications. Computational and mathematical methods in medicine.2015;1-24.
19. Liu, Jin, Min Li, Jianxin Wang, Fangxiang Wu, Tianming Liu, Yi Pan.A survey of MRI-based brain tumor segmentation methods. Tsinghua Science and Technology. 2014;19:578-95
20. Camps-Valls, Gustavo, and Lorenzo Bruzzone. Kernel-based methods for hyper spectral image classification. Geoscience and Remote Sensing, IEEE Transactions. 2005;43(6):1351-62.
21. JonasSjöberg , Qinghua Zhang , Lennart Ljung † Albert Benveniste , Bernard Delyon, Pierre-Yves Glorennec , Håkan Hjalmarsson , Anatoli Juditsky . ‡. Nonlinear black-box modelling in system identification: a unified overview. Automatica.1995;31(12):1691-724.
22. Zacharaki EI, Wang S, Chawla S, Soo Yoo D, Wolf R, Melhem ER, Davatzikos C..Classification of brain tumour type and grade using MRI texture and shape in a machine learning scheme. Magnetic Resonance in Medicine 2009;62(62):1609-18
23. Ahmed K, Karim G , Mohamed B, Nacéra BE, Mohamed A. A hybrid approach for automatic classification of brain MRI using genetic algorithm and support vector machine. Leonardo journal of sciences. 2010;17:71-82.
24. L. Lukas, A. Devos , J.A.K. Suykens, L. Vanhamme, F.A. Howe, C. Majós, A. Moreno-Torres M.Van Der Graaf, A.R. Tate, C. Arús, S. Van Huffel. Brain tumour classification based on long echo proton MRS signals. Artificial intelligence in medicine*,* 2004;31(1):73-89.
25. Henry Selvaraj, S. Thamarai Selvi, D. Selvathi, Laxmi P. Gewali, . Brain MRI slices classification using least squares support vector machine. International Journal of Intelligent Computing in Medical Sciences & Image Processing. 2007;1:21-33
26. Bauer, Stefan, Lutz-P. Nolte, Mauricio Reyes. Fully automatic segmentation of brain tumour images using support vector machine classification in combination with hierarchical conditional random field regularization. In Medical image computing and computer-assisted intervention–MICCAI, 2011;354-61
27. MacKay, David JC. The evidence framework applied to classification networks. Neural computation*,* ,1992;4:720-36.
28. Su Ruan , Stephane Lebonvallet , Abderrahim Merabet , Jean-marc Constans Tumor segmentation from a multispectral MRI images by using support vector machine classification. Biomedical Imaging: From Nano to Macro, *ISBI 4th IEEE International Symposium* .2007;1236-9.
29. Zhou, J., K. L. Chan, V. F. H. Chong, Shankar M. Krishnan. Extraction of brain tumor from MR images using one-class support vector machine. InEngineering in Medicine and Biology Society, IEEE-EMBS 27th Annual International Conference. 2006;6411-4
30. Nan Zhang, Su Ruan, Stéphane Lebonvallet, Qingmin Liao, Yuemin Zhu.
31. Kernel feature selection to fuse multi-spectral MRI images for brain tumor segmentation. Computer Vision and Image Understanding.2011;115(2):256- 269.