iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 Issue: III Month of publication: March 2024

DOI: https://doi.org/10.22214/ijraset.2024.58950

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue III Mar 2024- Available at www.ijraset.com

Brain Tumor Detection and Classification Via Kernel Support Vector Machine Using MRI Images

Ms. P. Divya Jenifar[1], Ms. R. Keerthana[2]
[1, 2]*Assistant Professor, Department of Biomedical Engineering, Sri Shakthi Institute of Engineering and Technology, Coimbatore - 62*

Abstract: The MR images of the brain requires automatic and accurate classification for medical analysis and interpretation nowadays. Numerous methods have been declared already in the previous years. In this paper we have presented a method which classifies the brain image of MRI into normal and abnormal brain tumor images. This method uses wavelet transform that extract features from images. The next step involves principle component analysis (PCA) that reduces the feature dimensions. These reduced features are then employed to a kernel support vector machine (KSVM). 180 images of the brain were collected from the diseased which contained 130 abnormal brain and 50 normal brain images. Four kernels of different types were performed.
Keywords: magnetic imaging resonance, wavelet transform, kernel support vector machine

I. INTRODUCTION

To produce high quality images of the anatomical structure of the human body, especially in the brain, Magnetic resonance imaging (MRI) is used. It provides clear information of anatomical parts for clinical diagnosis and biomedical research. For feature extraction from magnetic resonance brain images 2D discrete wavelet transform is the most effective tool. Because that allows analysis of images at various levels of resolution. It is due to the multi-resolution analytic property. In this principle component analysis is used to reduce the feature vector dimensions and to increase the discriminative power.

Classification of the image is the main purpose of this work. The brain magnetic resonance images are classified using Support vector machine and K-nearest neighbor methods which are supervised classification method. In unsupervised classification method fuzzy c-means algorithm is used. However, the classification accuracies of most of the existing methods were lower than 95%, so the goal of this paper is to find a more accurate method of classification.

In this paper, we used Kernel support vector machine (KSVM) which allows to fit the maximum-margin hyperplane in a transformed feature space.

Compared with other methods such as decision tree, Bayesian network and artificial neural network, KSVMs have significant advantages of high accuracy direct geometric interpolation etc.

II. METHODOLODY

A. Database

The datasets consists of T2-weighted MR brain image and 256 × 256 in-plane resolution, which were downloaded from the website of OASIS dataset (URL: http:// www.oasisbrains.org/). T2 model is chosen since T2 images are of higher-contrast and clearer vision compared to T1 and PET modalities.

B. Preprocessing

The first step in preprocessing is the Image resize. Image resizing is a process of changing pixel information, resizing an image involves changing the size of the pixels without cutting anything out. Image resizing to regulate the images to fixed scale (512×512) in order that it supports the classification with clear and accurate features. After that, conversion of images from RGB to gray level was done.

The next step is morphological operation of the image. Morphology is a set of image processing operations that process images based on size and shapes. Morphological operations applies a structuring element to an input image which creates an output image of the same size. In this step, processes like erosion, dilation and inversion are done.

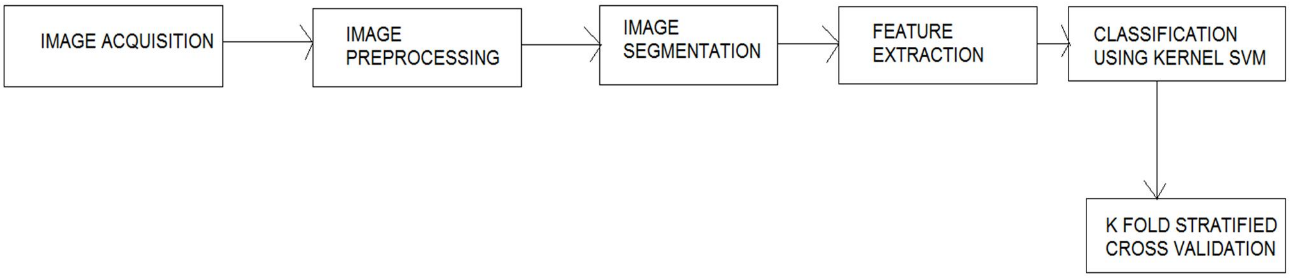


Fig 1. Block Diagram

C. Image Segmentation

Region growing method is the simplest region-based image segmentation technique. It is also classified as a pixel based image segmentation technique since it is involve the selection of initial seed points. The morphological operation is used for the extraction of boundary areas of the brain images. This operation is only rearranging the relative order of pixel value, not mathematical value, so it is suitable for only binary images. Dilation and erosion is basic operation of morphology. Dilation is add pixels to the boundary region of the object, while erosion is remove the pixels from the boundary region of the objects.

D. Feature Extraction

The formula of statistics feature for some of the required features in the proposed method is given below.
Mean (M). The mean of an image is calculated by adding all the pixel values of an image divided by the total number of pixels in an image.

$$M = \left(\frac{1}{m \times n}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y).$$

Standard Deviation (SD). The standard deviation is the probability distribution of an observed population and can serve as a measure of in-homogeneity. A higher value indicates better intensity level and high contrast of edges of an image.

$$\mathrm{SD}(\sigma) = \sqrt{\left(\frac{1}{m \times n}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (f(x, y) - M)^2}.$$

Entropy (E). Entropy is calculated to characterize the randomness of the textural image and is defined as

$$E = -\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y) \log_2 f(x, y).$$

Skewness (Sk). Skewness is a measure of symmetry or the lack of symmetry. The Skewness of a random variable X is denoted as Sk (X) and it is defined as

$$S_k(X) = \left(\frac{1}{m \times n}\right) \frac{\sum (f(x, y) - M)^3|}{\mathrm{SD}^3}.$$

Kurtosis (Sk). A random variable's probability distribution shape is described by the parameter called Kurtosis. For the random variable X, the Kurtosis is denoted as Kurt(X) and it is defined as

$$K_{urt}(X) = \left(\frac{1}{m \times n}\right) \frac{\sum (f(x, y) - M)^4|}{\mathrm{SD}^4}.$$

Energy (En). A parameter to measure the similarity of an image is energy. If energy is defined by Haralicks GLCM feature, then it is also referred to as angular second moment, and it is defined as

$$\mathrm{En} = \sqrt{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f^2(x, y)}.$$

Contrast (Con). Contrast is a measure of intensity of a pixel and its neighbor over the image, and it is defined as

$$C_{\mathrm{on}} = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (x-y)^2 f(x, y).$$

Inverse Difference Moment (IDM) or Homogeneity. Inverse Difference Moment is a measure of the local homogeneity of an image. IDM may have a single or a range of 15 values so as to determine whether the image is textured or nontextured.

$$\mathrm{IDM} = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \frac{1}{1+(x-y)^2} f(x, y).$$

Correlation (Corr). Correlation feature describes the spatial dependencies between the pixels and it is defined as

$$C_{\mathrm{orr}} = \frac{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (x, y) f(x, y) - M_x M_y}{\sigma_x \sigma_y},$$

E. 2D Discrete Wavelet Transform

The 2D discrete wavelet transform is used in multimedia application based on multimedia information retrieval system. Thus, a simple hierarchical framework for interpreting the image information is provided by wavelets. In this paper, level-3 decomposition via Harr wavelet was utilized to extract features. As we filter the image, the mask will extend beyond the image at the edges, so the solution is to pad the pixels outside the images.

F. K-Fold stratified Cross Validation

The mechanism is to create a K-fold partition of the whole dataset, repeat K times to use K −1 folds for training and a left fold for validation, and finally average the error rates of K experiments. Stratified K-fold cross validation was employed, where every fold has nearly the same class distribution. Parameter K varies from 3 to 10 with increasing, then the SVM is trained by each value. Finally, the optimal K value is selected corresponding to the highest classification accuracy.

G. Kernel SVM

In SVM, kernel function plays an important role. It will take an image data as an input and then transformed into required form. Since they help in determining various important things it is very significant in the image processing. Kernel SVMs has the following advantages: (1) work very well in practice and have been remarkably successful in some diverse fields as natural language categorization, bioinformatics and computer vision; (2) have few tunable parameters; and (3) training often involves convex quadratic optimization. Hence, solutions are global and usually unique, thus avoiding the convergence to local minima exhibited by other statistical learning systems, such as neural networks.

III. RESULT AND DISCUSSION

The algorithm was in-house developed via the wavelet toolbox, the biostatistical toolbox of Matlab 2011b. The open SVM toolbox and extended it to Kernel SVM which is applied to the MR brain images classification.

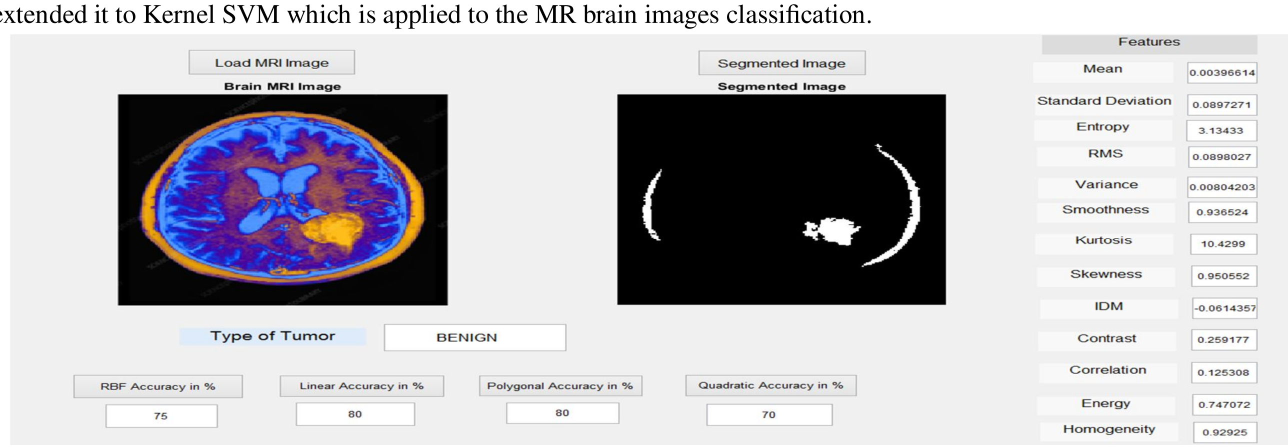


Fig 2. Output image

The output is shown using Matlab GUI, also known as apps, provide point-and-click control of the software applications, which eliminates the need for others to learn a language or type commands in order to run the application. It can share apps both for use within MATLAB and also as standalone desktop or web apps.

Total number of Images	Training (130)		Validation	
	Normal	Abnormal	Normal	Abnormal
180	30	100	20	30

TABLE 1. Setting of training and validation images

IV. CONCLUSION

Brain tumors are caused by abnormal and uncontrolled growing of the cells inside the brain. Treatment of a brain tumor depends on its size and location. Although benign tumors do not tend to spread widely, they can cause damage by pressing on areas of the brain if they are not treated early. To avoid manual errors in the classification process, an automated intelligent classification technique is proposed which caters the need for classification of image. In this proposed work classification techniques based on Support Vector Machines (SVM) are proposed and applied to brain image classification. Here the proposed brain tumor image segmentation based on discrete wavelet transform (DWT). The proposed work is tested with SVM classifier models. This automated intelligent system will results in the improvement of accuracy and reduces the error of MRI brain tumor.

REFERENCES

[1] Birare, Geetanjali, and V. A. Chakkarwar, "Automated detection of brain tumor cells using support vector machine", 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), pp. 1-4. IEEE, 2018.

[2] Srinivas, B., and G. Sasibhushana Rao, "Performance evaluation of fuzzy C means segmentation and support vector machine classification for MRI brain tumor", Soft computing for problem solving, pp. 355-367. Springer, Singapore, 2019.

[3] Mishra, S.K. and Deepthi, V.H., “Brain image classification by the combination of different wavelet transforms and support vector machine classification”, Journal of Ambient Intelligence and Humanized Computing, Vol. 12, No.(6), pp.6741-6749, 2021.

[4] Rampisela, T.V. and Rustam, Z., “Classification of schizophrenia data using support vector machine (SVM)”, Journal of Physics: Conference Series, Vol. 1108, No. 1, pp. 012044, IOP Publishing, 2018.

[5] Liu, J., Xu, H., Chen, Q., Zhang, T., Sheng, W., Huang, Q., Song, J., Huang, D., Lan, L., Li, Y. and Chen, W., “Prediction of hematoma expansion in spontaneous intracerebral hemorrhage using support vector machine”, EBioMedicine, 43, pp.454-459, 2019.

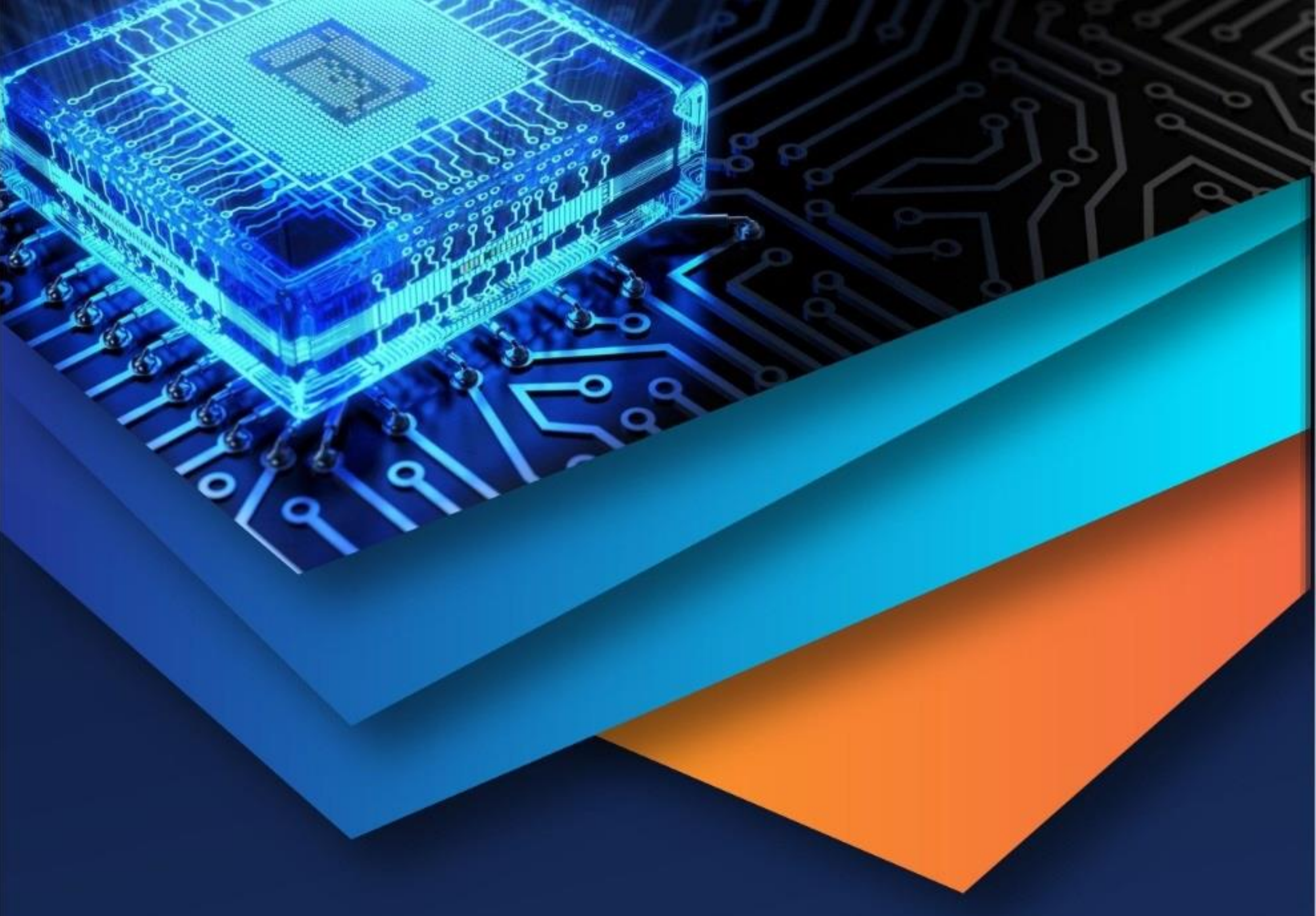
[6] Gurbină, Mircea, Mihaela Lascu, and Dan Lascu, "Tumor detection and classification of MRI brain image using different wavelet transforms and support vector machines", 42nd International Conference on Telecommunications and Signal Processing (TSP), pp. 505-508. IEEE, 2019.

[7] Hossain, T., Shishir, F.S., Ashraf, M., Al Nasim, M.A. and Shah, F.M., “Brain tumor detection using convolutional neural network”, 1st international conference on advances in science, engineering and robotics technology (ICASERT), pp. 1-6, IEEE, 2019.

[8] Gumaste, P.P. and Bairagi, V.K., “A hybrid method for brain tumor detection using advanced textural feature extraction”, Biomedical and Pharmacology Journal, Vol.13, No.(1), pp.145-157, 2019.

[9] Devkota, B., Alsadoon, A., Prasad, P.W.C., Singh, A.K. and Elchouemi, A., “Image segmentation for early stage brain tumor detection using mathematical morphological reconstruction”, Procedia Computer Science, Vol. 125, pp.115-123, 2018.

[10] Ejaz, K., Rahim, M.S.M., Rehman, A., Chaudhry, H., Saba, T., Ejaz, A. and Ej, C.F., “Segmentation method for pathological brain tumor and accurate detection using MRI”, International Journal of Advanced Computer Science and Applications, Vol. 9, No.(8), pp.394-401, 2018.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY