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AN EFFICIENT METHODOLOGY FOR ABNORMAL BRAIN AND STAGE DETECTION IN MRI IMAGES

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Abstract: A tumor is an unusual expansion of tissues replicating themselves in any part of the body. Various types of tumors are prevailing in the present day with different abnormalities and even diagnostic methods. A huge number of people having brain tumors due to incorrect judgment causes to death. MRI (Magnetic Resonance Imaging) is a method of diagnosis that is an assortment of radio frequencies, large magnet, and a computer to create comprehensive images of organs and structures within the body. MRI image is observed visually by the physician for finding & analysis of brain tumor. It is said that this method has less exactness while noticing the stage & size of the tumor. The present paper disclosures the finding of tumor stage in brain MR images with modified DWT+KPCA+KSVM. In order to create a more effective and successful method of finding and classifying the tumor, we attempted to deal the problem of analysis MRI brain images which act as an expert supporter of medical practitioners. The sole intention of the paper is to present a new approach of feature reduce and extraction where it unites the intensity, texture shape based description and classifications of a tumor as white matter, Gray Matter, CSF, abnormal and normal areas. The performances of the classifiers are evaluated in both the testing and training phases with various parameters. These classifiers are tested using a dataset of 38 MR brain images.

Keywords: Brain tumor, Magnetic Resonance Imaging (MRI), Classifier, Feature Extraction, Feature reduction

1. Introduction

In recent years, the rapid growth of death rate in humankind due to many brain diseases, among them the foremost is tumors is the major one. However, some of these brain tumors are identified to be either malignant or benign depending on the severity of their respective growth rate. The NBTF (National Brain Tumor Foundation) of United States has been observed that the brain tumor is there as on for one-fourth of all cancer deaths in children [1]. The key concept of the diagnosis is to find early and accurate inspection of the tumour for following the successful therapy and plan of handling. Even though, the diagnosis is critical and demanding task because of various discrepancies and difficulties of tumor categorisation in images.

Moreover the outcome of a recent piece of research provides compelling evidence that major work done on diagnosis and treatment of brain tumor. Basically in the segmentation process of brain tumor separation of the tumor soft tissues like edema as well as dead cells from normal brain tissues and solid tumors, such as White matter, Gray matter, and CSF [12] with the assistance of MR images or supplementary imaging modalities [13–16].The MR imaging is the critical and the most crucial improvement in the treatment of tumor is the non-invasive technique. In recent days, the usage of computer technology is important in every branch of learning including medicine. The usage of computer technology in medical announcements and judgements is a new approach and widely used in the areas like cancer research, gastroenterology, brain tumor and etc., so in other words MRI is the useful method for detection of abnormalities in soft tissues. The method is clearly locates tumor types, size and location and also used to find the different stage of tumor. In addition from extensive literature survey has revealed that availability of existed both semi and fully automated techniques for this application.

Coupled with the literature evidence several of them depend on computer based methods and comprise the idea of soft computing methods such as ANN and fuzzy logic techniques. Having said that, the most important problem is that if the techniques are accurate, the time requirement is high and vice-versa. In other words, both the merits of high accuracy and low convergence time are not concurrently available within the same technique. This has lead to the reduction of the efficiency of automated disease identification system. The proposed work consists of separate elements and each one individual element is accompanying with its own methods. The most important elements of this work are image database, pre-processing, feature extraction and reduction, as well as image classification.

The rest of the paper is structured as follows. In section II we describe related works. The section III discuss about Methods and Methodology. Sections IV present our Results and discussions. Finally in section V we concluded the paper.

2. Related works

In recent years, for the feature removal and classification of the brain MR images various techniques have been recommended by different researchers. Taking out essential feature from brain MR image is very important for further analysis and classification.

Chaplot et al. [3] have introduced a scheme for feature extraction and classification. To authenticate the introduced system they are taken a standard dataset of 52 brain MRI images. For feature extraction, they consider coefficient of level-2 approximation sub band of 2DDWT. Daubechies-4 (DAUB4) filter is used as decomposition filter. After getting the features they employed self-organizing map (SOM) and support vector machine (SVM) as classifier and they achieved higher classification rate for SVM with radial basis function (RBF) classifier i.e. 98% compared to the self-organizing map i.e. 94%.

Maitra and Chatterjee [4] have proposed a scheme for feature extraction and classification. For the feature extraction they have used slantlet transform (ST) and for the classification they used back-propagation neural network (BPNN) and archived ideal result. In [5] author presented a scheme, that uses ST for feature extraction and fuzzy c-means for classification and it have been shown that the proposed scheme outperformed related to previous one.

Selvaraj et al. [6] suggested a system for brain MR image classification. For classification they have used many classifier i.e. SVM classifier, Neural classifier, statistical classifier. Among all these classifier LS-SVM outperformed with 98% of achievement rate.

El-Dahshan et al. [7] recommended a technique. The suggested technique contains three stages i.e. feature extraction, feature reduction and classification. For feature extraction the rough calculation sub band of DWT is considered. Principal component analysis (PCA) isused for feature reduction and for the classification feed forward back-propagation neural network (FP-ANN) and k-nearest neighbor (k-NN) used as classifier and the achieved Zhang et al. [8] have proposed a scheme for classification. They have taken 160images (20 normal, 140 abnormal) to validate the scheme. For feature extraction level-3approximation component using Haar wavelet is used. After feature extraction, PCA is used for feature reduction and for the classification forward neural network is used and they achieved 98.75% classification accuracy.

Saritha et al. [9] suggested a scheme, in which they have used entropy of wavelet approximation component at level-8 computed along with SWP for feature extraction. For the classification they used Probabilistic neural network (PNN) and their results indicate that they achieve high success rate.

El-Dahshan et al. [1] suggested a hybrid technique, in which feed forward pulse-coupled neural network is applied for the segmentation of the brain images. For feature extraction they consider approximation component of DWT. For feature reduction they used PCA and for the classification they used back propagation neural network and achieved 99% accuracy.

3. Methods and Methodology

Otsu Threshold Algorithm: Thresholding creates binary images from grey-level images by setting all pixels below some threshold to zero and all pixels above that threshold to one. The Otsu algorithm defined in[10] is as follows:

i) According to the threshold, separate pixels into two clusters

ii) Then find the mean of each cluster.

iii) Square the difference between the means.

iv) Multiply the number of pixels in one cluster times the number in the other.

2D DWT: In case of 2D images, the DWT is practical to each dimension discretely. Here there are 4 sub-band (LL, LH, HH, and HL) images at each scale. The sub-band LL is used for next 2D DWT. The LL sub band can be regarded as the approximation component of the image, while the LH, HL, and HH sub bands can be regarded as the detailed components of the image.

Thus, wavelets supply an uncomplicated hierarchical outline work for construing the image information. In our algorithm, level-3decomposition via Harr wavelet was utilized to haul out features.

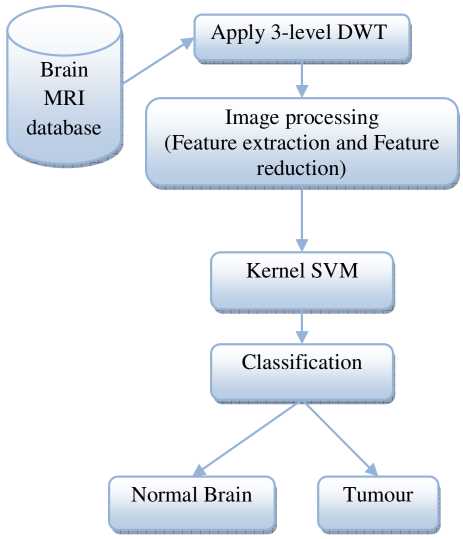


Figure 1. Block diagram of proposed work

Feature Extraction: The content of the image can be described by its features. The need for feature extraction is that the relevant information is extracted from the tumor region in order to perform the classification of tumor grades. The extracted feature should provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image into feature vectors. In this proposed method we extract the following features.

***Intensity features*:** Mean, Standard Deviation, Variance, Kurtosis, Skewness

Texture features: Entropy, Contrast, Correlation, Energy, and Homogeneity RMS, Smoothness, IDM

Feature Reduction: Extreme features raise calculation times and storage memory. Furthermore, they sometimes construct organization more complex, which is called the annoyance of dimensionality. It is compulsory to decrease the number of features. Here we use PCA (Principle Component Analysis) that can directly connected to SVD. It discovers a linear projection of high dimensional data into a lower dimensional subspace such as the difference maintained is maximized as well as the least square renovation error is minimized.

PCA steps (to reduce dimensionality from d to m):

- Center the data (subtract the mean).
- Calculate the d*x*d covariance matrix: $C = \frac{A^T A}{N}$
- Calculate the eigenvectors of the covariance matrix (orthogonal).
- Select the m eigenvectors that correspond to the heights meigen values to be the new space dimensions.
- The variance in each new dimension is given by the eigen values.
- Note that if we use all eigenvectors, we do loose any information (space rotation).

The problem of low-dimensional feature representation can be stated as follows:

Consider $X = (x_1, x_2, x_3, x_4 \ldots \ldots . x_i \ldots \ldots x_n)$ be treated as $n \times N$ data matrix.

Where n can be viewed as image pixels *(p, q)* present in brain image and total brain images in present in training set are denoted with *N.*

So therefore applying PCA that generates new set of variables so-called principal components, each principal component is linear combination of the original variables, all the principal components are orthogonal to each other.

So, if *X* is the original dataset, *Y* is the transformed dataset (both with size $m \times N$), and W^T is the linear transformation ($n \times m$) can be put in formulae as

$Y = W^T X$ ……………………… *(1)*

Here columns vectors are treated to be the eigenvectors comparable to the m principal eigen values work outby means of equation(2)

$\lambda e_i = S e_i$……………………… *(2)*

Where e_i and λ are denoted as eigenvectors and values of the matrix correspondingly.

Now the total scattering matrix *S* and also mean image of total samples considered are

$$s = \sum_{i=1}^{N} (x_i - \mu)(x_i - \mu)^T$$

$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i$ ……………………… *(3)*

It results in scatter of the transformed feature vectors after applying the linear transformation W^T can be arranged as

$$(y_1, y_2, y_3, y_4 \ldots \ldots . y_i \ldots \ldots y_n) = W^T S W$$

In PCA, the projection W_{opt} is picked to maximize the determinant of the total scatter matrix of the projected samples, i.e.

$$W_{opt} = arg^{MAX-w} |W^T S W|$$
$$= [W_1, W_2 \ldots . W_m] \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (4)$$

Where {*w,* \i=*1,* 2,….*m*} is the set of n-dimensional eigenvectors of S analogous to the *m* largest eigen values. So we can say that higher dimension (*n*-dimensional space) brain image is reduced to lower dimension (*m*-dimensional subspace) feature vector i.e. *m*<<*n.*

Kernel SVM: SVM are helpful in maintaining and developing the approaches and methods of identifying techniques from statistical learning theory. The main idea of employing SVM approach in resolving the classification problem is revealed in short as below:

a) With that assistance of non-linear mapping function input space vector is transformed to higher dimension space

b) Try to maintain maximum distance with the usage of hyper plane that is closest to training set points.

$w \bullet x + b = 0$.......................... (5)

where weight as well as bias parameters are denoted as w and b correspondingly.

Another key thing to depict the maximal margin hyperplane (MMH) the associated constraints must be satisfied:

$Minimize \frac{1}{2}\|w\| \; with \; y_i(w \bullet x_i + b) \geq 1$...... (6)

This is an exemplary nonlinear advancement issue with imbalance requirements. It can be settled by the Karush-Kuhn-Tucker (KKT) hypothesis by presenting Lagrange multipliers

$maximize \sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} y_i y_j a_i a_j x_i^T x_j$...... (7)

$subject \; to \; \sum_{i=1}^{l} a_i y_i = 0 \; and \; a_i \geq 0$...... (8)

The solution of w is:

$w = \sum_{i=1}^{l} a_i y_i x_i$...... (9)

The main nonzero outcomes depict those particular training data that are basic to outline the MMH and are called support vectors.

$x_i \epsilon R^n \rightarrow z(x) = [a_1\Phi_1(x), a_2\Phi_2(x) \ldots \ldots a_n\Phi_n(x)]^T \epsilon R^f$...... (10)

The KKT conditions transform to

$maximize \sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} y_i y_j a_i a_j K(x_i x_j$. (11)

$subject \; to \; \sum_{i=1}^{l} a_i y_i = 0 \; and \; a_i \geq 0$...... (12)

Finally one can suggest about Kernel SVMs have the subsequent benefits [11]:

(1) Work very well in all science and engineering and relevant fields

(2) Possesses tunable parameters and

(3) Training often consist of convex quadratic optimization.

4. Results and Discussions

The total work has carried out with the assistance of MATLAB2013b software. In order to understand it's been tested on brain MRI images including of abnormal and normal brain images. The abnormal brain MR images of the dataset consist of the several diseases as depicted in Fig. 2.

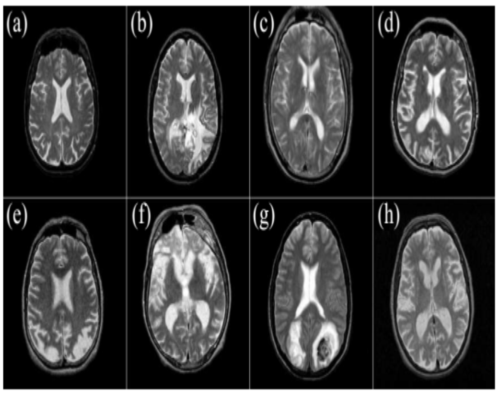


Figure 2. Sample of brain MRIs: (a) normal brain; (b) glioma (c) meningioma (d) Alzheimer's disease (e) Alzheimer's disease with visual agnosia (f) Pick's disease (g) sarcoma (h) Huntington's disease.

Table.1 discusses about the various stages of brain tumor and its features severity intensity tabulated to know the growth rate of brain tumor for early diagnosis of the patient.

Table 1. Significant Features used in the proposed work

Features Used	Benign Grade-II	Malignant Grade-III
Standard Deviation	0.0898	0.0898
Entropy	3.3601	3.3881
RMS	0.0898	0.0898
Kurtosis	6.2640	6.1105
Skewness	0.5470	0.3484

The investigational outcomes from the proposed method are revealed in Fig.3.

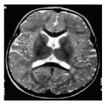
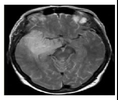
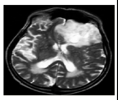
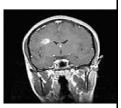
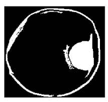
MRI Brain Image	Segmented	Tumour Stage	Accuracy
		Malignant -Type III	RBF: 90% Linear 90% Polynomial: 80%
		Benign-Type II	RBF 90% Linear 90% Polynomial: 80%
		Malignant -Type III	RBF: 70% Linear: 90% Polynomial: 90%
		Benign-Type II	RBF : 90% Linear: 90% Polynomial: 70%
		Malignant -Type III	RBF : 80% Linear: 80% Polynomial: 80%

Figure 3. Brain Tumor Stage and Grade detection for testing dataset

In the testing phase, the testing dataset is agreed to the proposed technique to discover the tumors in brain images. By using the performance metrics like specificity, sensitivity, and accuracy, the brain tumor classification accuracy of the proposed system is evaluated.

Sensitivity =TP/ (TP □FN) ×100

Specificity =TN/ (TN FP) ×100

Accuracy = (TN □TP)/ (TN □TP □FN □FP) ×100

Where, TP is short for True Positive, TN is little for True Negative, FN remains for False Negative and FP remains for False Positive.

To show the proposed work performance the comparison of several existed works incorporated in Table.2 and depicted in Fig.4. There are 3performancemeasures to relate to proposed work i.e. Sensitivity, Accuracy, and Specificity. Our Proposed work indicates enhanced Accuracy, Sensitivity, specificity from the conventional works as FCM, K-mean FCM. Table.2. shows the comparison different classification of techniques performance with that of proposed work.

Table 2. Comparison of classification Techniques

Technique used	Sensitivity	Specificity	Accuracy
FCM	96 %	93.3%	86.6%
K-Mean-FCM	80%	93.1%	83.3%
Proposed	97.8%	95.3%	88.6%

Computation time is yet another critical component to evaluate the classifier. The ideal opportunity for SVM preparing time not to be considered, on the grounds that the parameters of the SVM have unrevised after instruction. For each 256X256 image, the averaged computation times shown in the fig.5. However it is clear that feature extraction consumes more computation times than other.

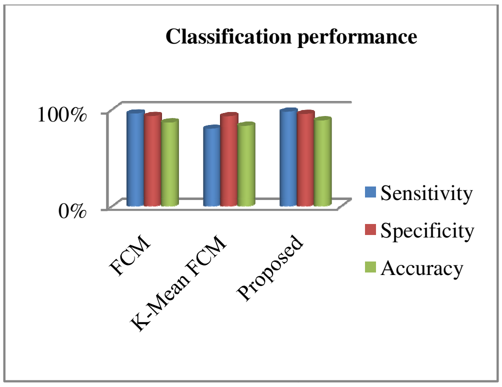


Figure 4. Comparison graph of classification performance

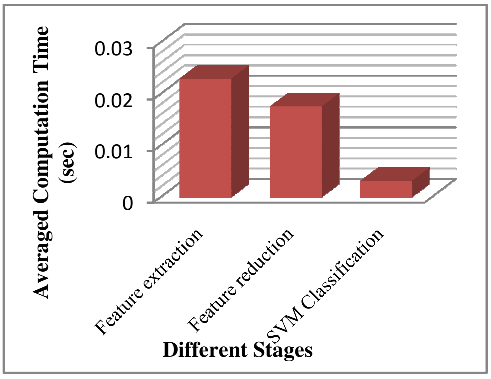


Figure 5. Computation times at different stages

All the 38 images were classified and recorded analogous computation time, computed the average value for different stages shown in Fig.5

5. Conclusion

In this paper, we carried out work with the assistance of modified DWT+KPCA+KSVM to classify whether the given input brain MRI image is normal or abnormal. In this work essential Intensity and Texture features are extracted for the purpose of classification. Also to know the Stage detection in MRI Images KSVM is employed, for high accuracy and low convergence time, performance of these classifiers on the collected dataset is measured with the aid of sensitivity, specificity and accuracy. The accuracy of the classifier mainly depends on the optimal features based on which it is trained. In this work, we introduced the kernel SVMs (KSVMs), which spread out original linear SVMs to nonlinear SVM classifiers by applying the kernel function to replace the dot product form in the original SVMs.

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