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Brain Tumor Classification and Segmentation using DTCW Transform, Back Propagation Neural Network and Spatial Fuzzy C-Means Clustering

Rahul Mapari, Sangeeta Kakarwal, Ratnadeep Deshmukh

Abstract*: A novel method is presented in this paper for finding brain tumor and classifying it using the back-propagation neural network is proposed. Spatial Fuzzy C-Means clustering is utilized for the segmentation of image to identify the influenced area of brain MRI picture. Automated detection of tumors in brain MR images is urgent in many diagnosis processes. Because of noise, blurred edges, the detection, and classification of brain tumor are very difficult. This paper presents one programmed brain tumor identification strategy to expand the exactness and yield and diminishing the determination time. The objective is ordering the tissues to three classes of typical, start and malignant. The size and the location tumor is very important for doctors for defining the treatment of tumor. The proposed determination strategy comprises of four phases, pre-processing of MR images, feature extraction, and classification. The features are extracted using Dual-Tree Complex wavelet transformation (DTCWT). Back Propagation Neural Network (BPN) is employed for finding brain tumor in MRI images. In the last stage, a productive scheme is proposed for segmentation depends on the Spatial Fuzzy C-Means Clustering. The performance analysis clearly proves that the proposed scheme is more efficient and the efficiency of the scheme is measured with sensitivity and specificity. The evaluation is performed on the image data set of 15 MRI images of brain.

***Keywords* : Spatial Fuzzy C-Means Clustering, Back Propagation Neural Network, MRI,Dual tree complex wavelet transformation.**

I. INTRODUCTION

An unusual development of the tissue in the brain is called brain tumor. The degree of tumor is decided by elements like-types of tumor, its location, its size and its condition of development. There are mainly two types of brain tumors, benign and malignant. Benign is non-cancerous belongs to the Low group; the development of abnormal tissues is slow. Also known as a non-metastatic tumor because, it does not contain a secondary stage. Malignant tumor is cancerous tumor. The development of abnormal cells is very fast. Also known as a metastatic tumor because, it contains a secondary stage of cancerous tumor. The development of the unusual cells is disorganized in metastatic type and it isa cancerous tumor. Brain tumor is one of the most hazardous and incurable disease. The Computerized classification and discovery of tumors in diverse medical images is inspired by the need of high exactness when managing human life. The help of the mechanized framework exceptionally requires in the field of therapeutic science as it can improve the proficiency of people in a space where false-pessimistic cases must be least. Filtering the cerebrum MRI pictures twice by people and the framework will improve the tumor recognition precision. Scanning the brain MRI images twice by humans and the system will definitely improve the tumor detection accuracy. The conventional method for checking and diagnosing diseases depends on detecting the presence of particular features by a human eyewitness. The process is time-consuming if the number of patients increased in some situation. Many techniques for automated diagnosis are developed in recent years to overcome the problems.

II. RELATED WORK

A. Submission of the paper

In the next subsections, various existing techniques are discussed which are utilized for brain tumor recognition and grouping.

[2] Noramalina Abdullah, Lee Wee Chuen, Umi Kalthum Ngah, Khairul Azman Ah-mad, in this article the classifications of brain tumors is done by using SVM. The exactness of algorithm with and without principle component analysis (PCA) is looked at.

[15] Vijay Wasule, Poonam Sonar, proposed method use LCM technique to extract image texture characteristics and store them as a vector function. The extracted characteristics are categorized using supervised SVM and KNN. The suggested system's precision is 96 percent for SVM and KNN and 86 percent for the clinical database and 85 percent for SVM and KNN and 72.50 percent for the Brats database respectively.

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* Correspondence Author
Rahul Mapari*, Computer Science and Engineering Department,Maharashtra Institute of Technology, Aurangabad, India. Email: rahulmapari@gmail.com
Sangeeta Kakarwal, Computer Science and Engineering Department, PES College of Engineering, Aurangabad, India. Email: s_kakarwal@yahoo.com
Ratnadeep Deshmukh, department of Computer Science and IT, Dr. Babasabheb Ambedkar Marathwada University, Aurangabad, India. Email: rrdeshmukh.csit@bamu.ac.in

[3] S Chaplot, Et al. In this paper, a new technique is proposed using wavelets as input to self-organizing maps of the neural network. Then SVM is used for classification of MRI images of the human brain. The technique proposed in this paper detects the brain tumor. The presented work is evaluated using a fifty two MRI brain images. 94 percent precision was obtained with the self-organizing maps of the neural network (SOM) and 98 percent with the vector support device.

[6] Jayalaxmi S. Gonal, Vinayadatt V. Kohir, The suggested technique in this article uses the Euclidean distance between the MR picture test feature vectors and the MR picture reference picture is evaluated. To classify the MR pictures as normal and abnormal pictures, these distances are further supplied to the k-Means classifier.

[1] D.Shridhar, Murali Krishna, The suggested technique in this article uses wavelets to decompose the input picture into approximate and detailed parts and texture feature extracts using a gray level co-occurrence matrix at three image resolution levels.

[4] Y. Zhang, L. Wu, A method is suggested in this article to classify a specified MR brain picture as ordinary or abnormal. Wavelet transformation is used in this technique to obtain characteristics from pictures, followed by the application of the principle component analysis (PCA) to decrease the dimensions of characteristics. The pictures are presented to a kernel support vector machine with decreased sizes. K-fold stratified cross-validation approach is used to improve Kernel support vector machine generalization. Four kernels assessed the method and it is noted that the GRB kernel achieves the greatest precision of classification than others.

[5] S A Dahshan, Et al. The proposed technique is to use the pulse-coupled neural feedback network to segment images, the DWT to extract features, the PCA to reduce the wavelet coefficients dimensionality, and the feed-forward neural network to classify brain MRI images into normal or abnormal types. The classification accuracy for both training and testing images is very high, i.e. around 99%.

[7] Pauline John, The suggested technique categorized brain tumors to ordinary, benign and malignant brain tumor in three phases of, (1) wavelet decomposition, (2) extraction of textural features, and (3) classification. The wavelet DWT and Daubechies is used to obtain characteristics such as entropy, energy, contrast, etc. For further classification and tumor detection, the resultsof co-occurrence matrices are then fed into a PNN. The precision of the technique proposed is very high. [8] SA Dahshan, AM Salem, TH Younis. The suggested technique consists of three phases, extraction characteristics, decrease of dimensionality and classification. MRI-related characteristics are obtained using discrete wavelet transformation in the first phase. In the next stage, PCA reduces the features of MRI images and in the last step, two classifiers were developed based on supervised machine learning. The first classifier relied on artificial neural network (FP-ANN) feed-forward back-propagation and the second classifier focused on k-nearest neighbor (k-NN). The classifiers were used to classify brain into normal or abnormal MRI.This method assessment demonstrates that the hybrid technique suggested is efficient compared to other techniques.

[10] Evangelia I., The suggested system comprises of extraction, choice of features and classification of several phases. The characteristics obtained include tumor shape and characteristics of intensity as well as characteristics of rotation invariant texture. The choice of subsets of features is performed using SVM with elimination of recursive function.

[12] J.Nivethitha, M.Machakowsalya, R.Lavanyadevi, A.Niranjil Kumar, in this article the neural network is utilized to categorize tumor as normal, malignant or benign. In presented work, the extraction of features is accomplished with the Gray Level Co-Occurrence Matrix. PCA is used for Image recognition and image. Using PCA the dimensionality is also decreased. PNN is used for Classification. K-means clustering algorithm is used for Segmentation and also to find out the affected location. PNN is discovered to be the fastest method and to provide excellent classification precision as well..

[9] Yudong Zhang, ZhengchaoDong, Lenan Wu, Shuihua Wanga, in this paper, They have a technique of classifying the brain picture as ordinary or abnormal using a neural network. DWT extracts features, and PCA reduces size and characteristics. The characteristics are then transmitted to BPNN, which adopts the scaled conjugate gradient (SCG) to locate the NN's optimum weights. On both training and test pictures, the classification accuracies are 100 percent, and the computation time is also very small.

[13] Ali Ismail Awad, Et al., A two-stage method for the identification and classification of brain tumors is suggested in this article. The system suggested classifies the picture of the brain MRI into a standard or abnormal class. The tumor form is categorized as benign or ma-lignant in the second phase. MRI pictures are segmented by clustering of K-means, extraction of features using discrete wavelet transform (DWT), decrease of features by PCA. SVM is used to classify in two stages.

[14] S.K. Shil, in this scheme, K- means clustering is used for segmentation, DCT and PCA is used for feature extraction and reduced features are submitted to SVM for classification. Performance evaluation is done using specificity, sensitivity and accuracy parameters.

[11] Praveen, Amritpal Singh, a method based on the SVM and fuzzy c-means is suggested. The picture is improved with contrast enhancement and mid-range stretch in the preprocessing phase. For skull stripping, dual thresholding and morphological operations are used. FCM is used for brain MRI image segmentation to identify the place of the tumor in the MRI picture.

GLRLM is used to extract function from the brain picture, after which SVM method is applied to classify brain MRI pictures, providing an accu-rate and more efficient outcome for classifying brain MRI pictures.

III. PROPOSED ALGORITHM

The suggested method is aimed at detecting and classifying brain tumors using the neural network model and SFCM and back propagation.The suggested technique of diagnosis has phases like MR image pre-processing, extraction, detection and classification of features.

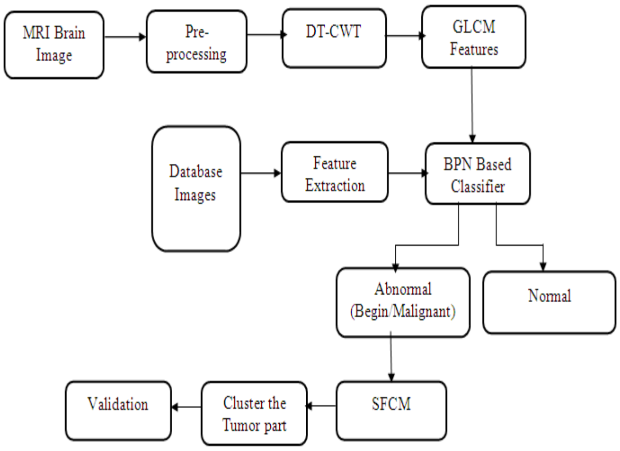

Fig. 1. System Architecure

A. Preprocessing

Preprocessing of the picture is performed to improve the picture in order to obtain more precise outcomes in subsequent phases. It involves numerous activities that do not improve the content of picture data. It is performed to enhance the job of further processing and analysis. The first step in this process is to generate a noiseless image. For the effective brain tumor detection, impulse noise is eliminated using median filtering technique.

B. Dual Tree Complex Wavelet transform

In the extraction method of the feature, to identify the tumor in the brain MRI pictures, we need to obtain the characteristics from the outliers. The suggested technique, together with eight kinds of characteristics, convert ex-tracts dual tree complicated wavelet based function extract. They are texture characteristics and intensity-based characteristics[27].

Two true wavelet trees, each capable of ideal recon-struction (PR), are used in dual-tree. The real part of the transform is produced by one tree while the additional is used to produce complicated portion. $R_0(k)$, $R_1(k)\}$ is an exposed pair of Quadrature Mirror Filter (QMF) in the real-coefficient branch of assessment. $J_0(k)$, $J_1(k)\}$ is another QMF pair in the branch of the study for the complicated portion. The filters used for DTCWT are designated as linear phase supporting the condition of Perfect Reconstruction (PR) and are combined in such a way that the transform's final result is analytical.

$$\Psi(t) = \Psi_R(t) + j\Psi_j(t) \quad (1)$$

Where the wavelet produced by two DWTs are $\Psi_R(t)$ and $\Psi_j(t)$. Furthermore, both low-pass filters $R_0(k)$ and $J_0(k)$ must have a property in order to form a rough Hilbert transform couple with the respective wavelets.

$$\Psi_j(t) \approx H\{\Psi_R(t)\} \quad (2)$$

One of the two low-pass filters must be approximately half-sample shift to the other for this purpose

$$J_0(k) \approx R_0(k-0.5) \Rightarrow \Psi_j(t) \approx H\{\Psi_R(t)\} \quad (3)$$

These half-example defer principles to around move invariant wavelet change.

The DTCWT has following characteristics:

• In two and greater dimensions, it is almost invariant shifting and directionally selective.

• This is achieved by a redundancy factor of only 2d for d-dimensional signals, substantially lower than the non-decimated DWT.

C. Back Propagation Network

Four steps in the BP algorithm:
i) Feed forward computing
ii) Back to output layer
iii) Back to hidden layer
iv) Updating of weights

- The process will stop automatically if the error function value is too low. The following figure is the three-layered network notation, BPN network advantages and disadvantages:
- Training a BPN / GRNN network is generally much quicker than a multilayer perceptron network.
- BPN / GRNN networks are often more precise than perceptron multi-layer networks.
- Outliers (wild points) are comparatively insensitive to BPN / GRNN networks.
- BPN networks produce precise target likelihood ratings.
- Networks of BPN approach optimal classification of Bayes.
- BPN / GRNN networks are slower when classifying fresh instances than multilayer perceptron networks.
- Networks requiring BPN / GRNN Removing unnecessary neurons

One of the drawbacks of BPN models compared to multilayer perceptron networks is that BPN models are big because each training line has one neuron. This is why, when using scoring to forecast values for fresh rows, the model will run slower than multilayer perceptron networks.

DTREG offers an option to cause unnecessary neurons to be removed from the model after the model was built.

There are three advantages to removing unnecessary neurons:

1. The stored model's size is decreased.

2. During scoring, the time needed to apply the model is decreased.

3. Neuron removal often increases the model's precision.

Iterative method is the method of removing unnecessary neurons.

Leave-one-out validation is used with each neuron removed to assess the model's mistake. Then the neuron that creates the least error rise (or potentially the greatest error decrease) is separated from the model. With the remaining neurons, the process is repeated until the stop criterion is reached.

There are three steps to guide the removal of neurons that can be chosen:

1. Minimize error–If this option is chosen, DTREG will remove neurons as long as there is a steady or decreasing departure error. It stops when a neuron is discovered whose removal would boost the mistake above the minimum discovered.
2. 2. Minimize neurons–If this option is chosen, neurons will be removed by DTREG until the leave-one-out error with all neurons exceeds the model error.

3. 3. #of neurons–Upon selecting this choice, DTREG decreases the least important neurons until only the designated amount of neurons stay.

A description of the BPN classifier derivation has been provided. BPNs were used for issues with classification. The BPN classifier provided reasonable accuracy, very less training time, robustness to modifications in weight, and small retraining time.

D. Spatial Fuzzy C-Means Clustering

The Spatial Fuzzy C-Means (SFCM) algorithm is used to determine the suspect region from the picture of the brain MRI. This method offers a nice outcome of segmentation. Overall, with a significant quantity of advantages, a fuzzy segmentation technique, particularly this is more efficient. It enables pixels to have a relationship with various nodes with variable degrees of membership, unlike difficult clustering techniques, such as k-means algorithm, etc., which attribute pixels solely to one cluster. Although this is a very common method for unsupervised clustering, it has some severe disadvantages as it is highly susceptible to artifacts of noise and imaging. Because of bad initialization, it can also produce ideal local solution. [28][29].

The Fuzzy C-Means allocates pixels to different clusters depending on the pixels belonging to a specific cluster's fuzzy member-ship feature.

Suppose,a picture organized in a 1-D matrix as $X=[x_1,x_2,\ldots\ldots x_N]$, where x_i is the size of the pixel volume or the size of the function and N is the complete pixel in the picture. The task of FCM is to separate the pixels into c clusters. The cost function is defined in (4) of the standardFCM[30].

$$j=\sum_{j=1}^{N}\sum_{i=1}^{c}u_{ij}^{m}\left\|x_j-v_i\right\|^2 \quad (4)$$

Pixel x_j's membership value in i^{th} cluster is denoted as u_{ij}, cluster core is v_i, and parameter is m which regulates the outcome of the partition. The cluster and membership values center updates are performed in accordance with equation (5) and (6).

$$u_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_j-v_i\right\|}{x_j-v_k}\right)^{\frac{2}{(m-1)}}} \quad (5)$$

$$v_j=\frac{\sum_{j=1}^{N}u_{ij}^{m}x_j}{\sum_{j=1}^{N}u_{ij}^{m}} \quad (6)$$

Neighborhood pixel data is used in SFCM. The neighborhood pixels may very well have the same value and are of the same cluster. This idea is not taken into account in the FCM norm. SFCM uses temporal data to define a temporal function[3] as described in (7).

$$h_{ij}=\sum_{k\varepsilon NB(x_j)}u_{ik} \quad (7)$$

The default window above is $NB(x_j)$ on the pixel x_j focused picture. The window volume may be 3 by 3 or 5 by 5 but we've only regarded 5x5 window in this. The visual h_{ij} is described as the probability of the i^{th} cluster belonging to a pixel x_j.A greater value shows that this cluster resemble stomany of the neighborhood pixels of a core pixel being considered. By integrating the spatial feature into the membership function, the normal FCM is altered. In (8), which is copied from (6), the altered membership function is described.

$$u_{ij}=\frac{u_{ij}^{p}h_{ij}^{q}}{\sum_{k=1}^{c}u_{kj}^{p}h_{kj}^{q}} \quad (8)$$

Here, bounds are q and p that determines effect of the initial membership function and the temporal feature in calculating the fresh membership functions respectively. When SFCM degenerates to standard FCM when p=1 and q=0.In two phase iteration, the spatial FCM works. The membership values are determined in the first phase using the traditional Fuzzy C-Means. These membership values are used in the spatial function calculation. The second stage uses (2) to calculate the new member-ship feature. The iteration is over after the convergence condition has been attained. The convergence limit can be set when there is no shift in the last two consecutive iterations between two cluster centers. After the iteration is finished, defuzzification method is launched by assigning to that cluster a pixel with a maximum membership function[31][32].

IV. RESULTS AND DISCUSSIONS

The dataset entry comprises of 256* 256 pixels of MR brain pictures (Fig.2). These are collected from the portal of the Harvard Medical School(“http:/med.harvard.edu/AANLIB/”)[5].

The quantity of brain MRI images in the input data set is 15. In dataset 4 images are normal brain images and 11 are abnormal brain images. Back propagation neural network with spatial fuzzy C-means clustering is used in this article for classification and segmentation of brain tumors. The back propagation neural network is trained using 15 brain MRI pictures and is then tested using 15 brain MRI pictures.

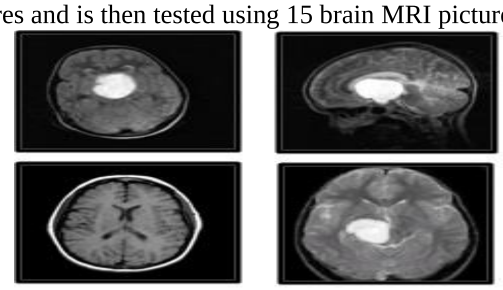

Fig. 2.Sample Brain MRI Images from used dataset

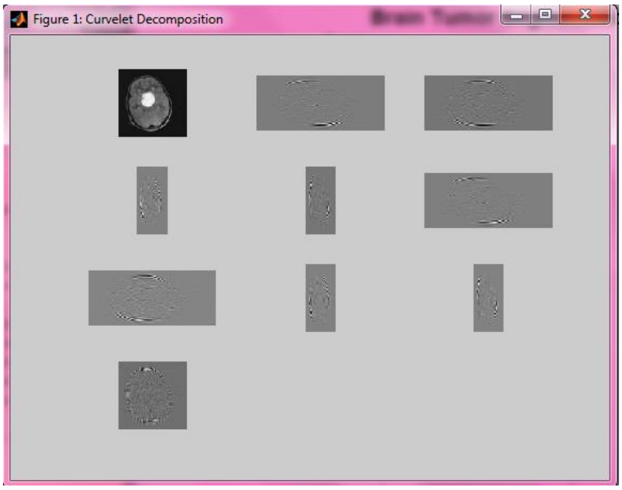

Fig. 3.Curvelet decomposition

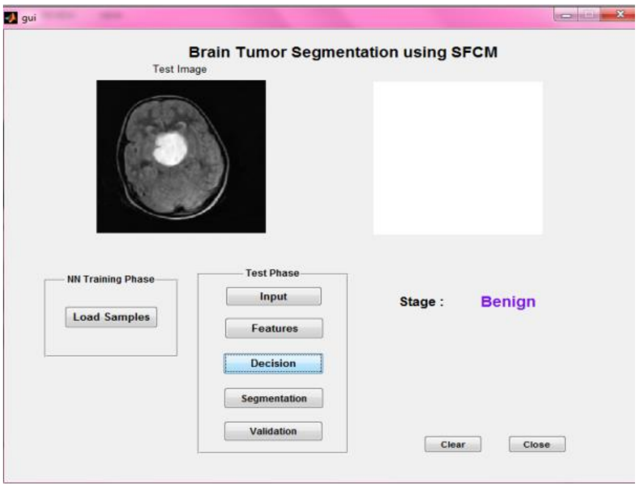

Fig. 4.Decision

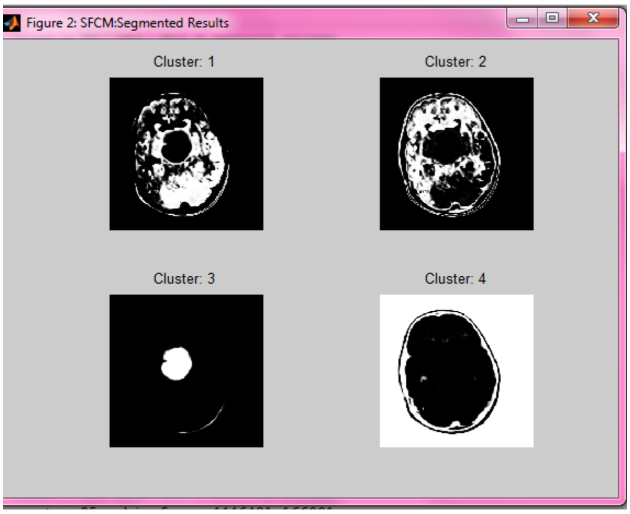

Fig. 5.Segmentation result

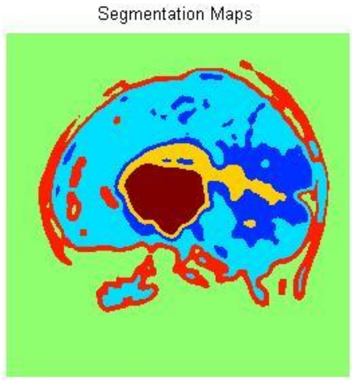

Fig. 6.Segmentation Maps

Following table shows the classification rate of proposed scheme and KNN classifier.

Table I. Performance Evaluation of Classifiers

Parameter/Classifier	**BPN**	**KNN[15]**
Sensitivity	85.7143	84
Specificity	100	88
Accuracy	90.9091	86

Following table shows performance of SFCM algorithm with the segmentation time, cautious tumor area and no. of affected cells.

Table 1. Performance of SFCM algorithm with the segmentation time, cautious tumor area and no. of affected cells.

Image	regular/ Abnormal	Segmentation Time(in sec)	Tumor Affected Area in Sq.MM	No. of Defected Cells
1	Benign	4.14	38.1834	20919
2	regular	regular	regular	regular
3	regular	regular	regular	regular
4	regular	regular	regular	regular
5	regular	regular	regular	regular
6	Benign	4.3802	12.2951	2169
7	Benign	4.26.23	11.7057	1966
8	Benign	4.1959	12.0778	2093
9	Benign	4.51	5.56283	444
10	Malignant	3.0085	17.04	4169
11	Malignant	3.3352	36.5151	19131
12	Malignant	4.4901	11.7532	1982
13	Benign	6.9545	13.3052	2540
14	Benign	7.6683	14.52	3025
15	Benign	6.1057	21.4328	6591

A. Evaluation parameters

Sensitivity: Sensitivity is used to find the ability of scheme to determine abnormal instances. Specificity is used to find the ability of scheme to determine regular instances. Accuracy is the ratio of right classifications to the complete amount of trials for classification. This method of brain tumor classification has been performed on various normal, benign and malignant real MR images and the specificity, sensitivity and accuracy of the classifier has been calculated, using the equations given below.

Sensitivity = (Tp./(Tp + Fn))*100

Where,

Tp = True Positive: Number of appropriately classified cases

Fn = False negative: Number of mistakenly classified cases

Specificity = (TN/(TN + FP))*100

Accuracy= (Correct cases/Total)*100

V. CONCLUSION

This paper proposes and implements a fresh technique for brain tumor identification, classification and segmentation. This latest technique is the BPNN and SFCM blend. The back propagation neural network is used to categorize whether the brain is normal or abnormal and spatial fuzzy C-means clustering is used to position and find the exact size of tumor in MRI image using segmentation. We implements dual tree complex wavelet transform that is used efficiently to extract characteristics from pictures of brain MRI. After successive experimentations we get the classification accuracy of 90.91% with 100% sensitivity rate and 85.71% specificity rate. More than 90% precision of outcomes demonstrates the capacity of the suggested technique for optimum extraction of features and effective classification of brain tumors.

REFERENCES

1. D.Shridhar, Et al., "Brain Tumor Classification Using Discrete Cosine Transform and Probabilistic Neural Network", 2013 Internationa Conference on Signal Processing, Image Processing and Pattern Recognition, 2013 IEEE.
2. N Abdullah, Et al., "Improvement of MRI Brain Classification using Principal Component Analysis", 2011 IEEE International Conference on Control System, Computing and Engineering, 2011 IEEE.
3. S Chaplot, Et al., "Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network", Biomedical Signal Processing and Control 1, pp. 86-92,2006 Elsevier.
4. Y. Zhang, Et al., "An Mr Brain Images Classifier Via Principal Component Analysis And Kernel Support Vector Machine", Progress In Electromagnetics Research, Vol. 130, pp.369-388, 2012.
5. El-Sayed A. Et al., "Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm", Expert Systems with Applications 41,pp.5526-5545, 2014 Elsevier.
6. JS. Gonal, "Classification of Brain MR Images using Wavelets Texture Features and k-Means Classifier", International Conference on Electrical, Electronics, Signals, Communication and Optimization2015 IEEE.
7. P John, "A Classifier to Detect Tumor Disease in MRI Brain Images", 2012 IEEE/ACM International Conference on Advances in Social Network Analysis and Mining, 2012 IEEE.
8. Sayed A. Dahshan, Et al., "A Hybrid Technique For Automatic Mri Brain Images Classification", Studia Univ. Babes-Bolyai, Informatica, Volume LIV, Number 1, 2009.
9. Y Zhang, Et al., "A hybrid method for MRI brain image classification", Expert Systems with Applications, (2011), pp. 10049-10053, Elsevier.
10. E I. Zacharaki, Et al., "MRI-Based Classification Of Brain Tumor Type And Grade Using SVM-RFE", 2009 IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2009 IEEE
11. Praveen, Et al., "Detection of Brain Tumor in MRI Images, using Combination of Fuzzy C-Means and SVM", International Conference on Signal Processing and Integrated Networks, 2015 IEEE.
12. R.Lavanyadevi, Et al., "Brain Tumor Classification and Segmentationin MRI Images using PNN", 2017 International Conference on Electrical, Instrumentation and Communication Engineering.
13. M Khaled Abd-Ellah, Et al., "Design and Implementation of a Computer-Aided Diagnosis System for Brain Tumor Classification", 2016 28th International Conference on Microelectronics (ICM) 978-1-2016 IEEE.
14. S.K. Shil, Et al., "An improved brain tumor detection and classification mechanism", 2017 International Conference on Information and Communication Technology Convergence,2017 IEEE.
15. Vijay Wasule, Et al., "Classification of Brain MRI Using SVM and KNN Classifier", 2017 IEEE 3rd International Conference on Sensing, Signal Processing and Security,2017 IEEE.

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16.KH Ghazali, Et al., "Feature Extraction Technique using Discrete Wavelet Transform for Image Classification", The 5th Student Conference on Research and Development, 2007 IEEE.
17.Y.D. Zhang, Et al., "A New Classifier For Polarimetric Sar Images", Progress In Electro magnetics Research, PIER 94, 83-104, 2009.
18.Pasi Luukka , "Classification Based on Fuzzy Robust PCA Algorithms and Similarity Classifier", Expert Systems with Applications, Volume 36, Issue 4, May 2009, Pages 7463-7468, Elsevier.
19.M. Saritha, Et al., "Classification of MRI brain images using combined wavelet entropy based spider web plots and probabilistic neural network", Pattern Recognition Letters Volume 34, Issue 16, 1 December 2013, pp. 2151-2156.
20.V. Anitha, S. Murugavalli, Brain tumour classification using two-tier classifier with adaptive segmentation technique", IET Comput. Vis., pp. 1-9, The Institution of Engineering and Technology 2015.
21.I Guyon, Et al., "Gene Selection for Cancer Classification using Support Vector Machines", Machine Learning, January 2002, Volume 46, Issue 1-3, pp 389-422.
22.O Sahu, Et al., "Classification of Magnetic Resonance Brain Images using Bi-dimensional Empirical Mode Decomposition and Autoregressive Model", Biomed EngLett (2015) 5:311-320, Springer.
23.Amer Al-Badarneh, Et al., "A Classifier to Detect Tumor Disease in MRI Brain Images", 2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, 2012 IEEE.
24.A Vidyarthi, N Mittal, "Comparative Study for Brain Tumor classification on MR/CT images", https://www.researchgate.net/publication/259531035_Comparative_Study_for_Brain_Tumor_Classification_on_MRCT_Images.
25.M Hamoud Al-Tamimi, Et al., "Tumor Brain Detection Through MR Images: A Review Of Literature", Journal of Theoretical and Applied Information Technology, Vol. 62 No.2, 2014, pp. 387-403.
26.Moitra D Et al., "Review of Brain Tumor Detection using Pattern Recognition Techniques". International Journal of Computer Sciences and Engineering, Vol 5, Issue 2, pp. 121-123.
27.Deepa, Et al., "Classification of Brain Tumor by DEA-ANN with DTCWT Based Features and Mixture Model Based Brain MRI Segmentation", Global Journal of Pure and Applied Mathematics, Volume 13, Number 7 (2017), pp. 3919-3935
28.S Kr Adhikari, Et al.," A Spatial Fuzzy C-means Algorithm with Application to MRI Image Segmentation", 2015 Eighth International Conference on Advances in Pattern Recognition 2015 IEEE.
29.Th. Ibungomacha Singh, Et al., "Image segmentation using spatial fuzzy C means clustering and grey wolf optimizer", 2016 IEEE International Conference on Computational Intelligence and Computing Research.
30.C Huang , Et al., "MR Image Segmentation Based On Fuzzy C-Means Clustering and the Level Set Method", International Conference on Fuzzy Systems and Knowledge Discovery,2008.

AUTHORS PROFILE

Rahul Mapari, ME(CSE), working as an Assistant Professor in Computer Science and Engineering Department, Maharashtra Institute of Technology, Aurangabad, India. Published 15 papers in international journals. Working in the area of Medical image processing. Completed Master of Engineering from Swami Ramanand Tirtha Marathwada University, Nanded(MS) and peruing Ph.D. in Computer Scince and Engineering at Dr. Babasaheb Ambedkar Marathwada University, Aurangabad. Recognize by Infosys as Bronze partner Faculty in 2016,2017,2018. A Lifetime member of Computer Society of India and CRSI. Taught various courses at under graduate and post graduate level like Operating System,Computer Fundamentals and Programming,Software Testing and Quality Assurance,,Relational Database Management System,Web Page Design, Data Mining and Warehousing,Discrete Mathematics Structures, Data Communication and Computer Network,Programming in VB.Net,Computer Networks,User Interface Technology Object Oriented Programming,.

Sangeeta Kakarwal, working a Professor in Computer Science and Engineering Department, PES College of Engineering, Aurangabad, India. Completed the Ph.D. in the subject of Computer Science and Engineering from Dr. Babasaheb Ambedkar Marathwada University, Aurangabad. Woking in the area of Image processing and pattern recognition. Published more than 15 papers in reputed international journals. More than 15 papers are published in various international conference proceedings. A life time member of ISTE and also the member of Computer Society of India.

Ratnadeep Deshmukh, working as a Professor in the department of Computer Science and IT, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad. Woking in the area of Image processing and pattern recognition. Published more than 50 papers in the reputed international journals. More than 20 papers are published in various international conference proceedings. Worked on the UGC sponsored project titled "Development of Database and Automatic Recognition System for Continuous Marathi Spoken Language for Agriculture Purpose in Marathwada Region". Working as an editor in chief, reviewer for many reputed international journals and conferences proceedings. A Lifetime member of many associations like FIETE, CSI, ISTE, ACEEE, CSTA and also the member of IEEE. Published more than 9 books with reputed publishers.