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Detection and Classification of Brain Tumor from MRI Medical Image using Wavelet Transform and PSO based LLRBFNN Algorithm

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Abstract— It is a difficult and complex task for a radiologist or clinical practitioner to segment, detect, and extract infected tumor area and classify the type of tumor from magnetic resonance (MR) images. This paper presents a PSO (Particle Swarm Optimization) based LLRBFNN (Local Linear Radial Basis Function Neural Network) model to classify and detect brain tumors into malignant (cancerous) and benign (noncancerous). In this paper we have used wavelet transform to improve the performance of MR image segmentation process and feature extraction. For the validation of the proposed PSO based LLRBFNN model, the machine learning approach support vector machine (SVM) and LMS (Least Mean Square) based LLRBFNN classifier also investigated. The research work follows the steps such as feature extraction out of which relevant features are considered for the research work. In the second step the features are fed as input to the proposed PSO based LLRBFNN Model for the classification task. In the third step the machine learning approach SVM and LMS based LLRBFNN has been applied for classification task and the results are compared. It is found that the proposed model takes less computational time than the SVM and LMS based LLRBFNN machine learning approach. In contrast to classification results the proposed model gives better classification results. Based on accuracy it is also noticed that the proposed model shows better performance in accuracy and quality analysis on MRI brain images.

Keywords—SVM, Wavelet Transform, DWT, PSO, LLRBFNN, Brain tumour, Feature extraction

I. INTRODUCTION

According to the medical study, the encephalon tumor (Brain Tumor) is the irrepressible magnification of cancerous cells in the encephalon and benign, malignant are classes of encephalon tumor. The structure of benign tumor does not contain active cancer cells, whereas malignant encephalon tumors have active cells and it has diversified structure [1]. The benign tumors are kenned as low-grade tumors, categorised as gliomas and meningiomas. On the other hand, malignant tumors are high-grade tumors such as glioblastoma and astrocytomas. According to the World Health Organization (WHO) and American Brain Tumor Association (ABTA) **[2],** the benign and malignant tumors utilizes a grading system from grade I to grade IV. The benign tumors comes under grade I and II which have a slow magnification, and grade III and IV shows malignant tumors own an expeditious magnification of tumors. Glioblastoma Multiform (GBM) is the most mundane truculent cancer that commences within the encephalon initially, and malignant intracranial tumor representing 30% of primary encephalon tumors [3]. The survival rate of patients is only 10 to 14 months after diagnosis. The symptoms include headaches, personality changes and stroke. This may withal causes to insensateness. For the rate of survival, the early detection and relegation of encephalon tumors is very consequential in clinical practice.

Due to the size and location variability and complexity of tumors in the human brain, MRI (Magnetic resonance Imaging) brain tumor images classification becomes a difficult task. Magnetic resonance imaging (MRI) is the most widely used medical imaging technique for identifying the location and size of brain tumours. More advanced MR techniques like diff usion-weighted MRI, perfusion-weighted MRI, and chemical shift imaging (CSI) are promising in the characterization of brain tumours as they give potentially more physiological information **[3]**. In present days, the MR images are processed through statistical morphological analysis and thresholding techniques. In recent days many researchers have proposed different models such as ANN, PNN, and MLN etc. with different algorithm for the classification of brain tumors based on different sources of information.

This paper introduces an efficient model for brain tumor classification, where, the real Magnetic Resonance (MR) images are classified into normal, non-cancerous (benign) brain tumor and cancerous (malignant) brain tumor. In this research work we propose a PSO based LLRBFNN model for brain tumor classification of benign and malignant tumors.

Our goal is to achieve a better accuracy results in considering the two types of tumors through a combination of different machine learning techniques for image segmentation, feature extraction and classification. The proposed model has the potentiality of classifying the tumor and will assist clinical diagnosis. In the pre-processing steps it is necessary to analyse the regions of interest (ROIs). However, in this research work we take into account the location of the tumor in the MR image. To describe precisely the boundaries of the ROIs, Image segmentation has been done. In this work the tumors are outlined and labelled with consistency. Radiologists performing Segmentation manually but the manual method is time consuming and its accuracy depends highly on the domain knowledge of the radiologist.

The proposed method follows the steps such as (1) feature extraction by wavelet transform (2) LLRBFNN Model design (3) classification and (4) classification result comparison with SVM and LMS based LLRBFNN model. We have employed Discrete Wavelet Transform to decompose the MR image into different levels of approximate and detailed coefficients. From the coefficient the gray level co-occurrence matrix is formed, out of which the statistical features such as such as energy, kurtosis, correlation, mean, standard deviation, skewness, smoothness and entropy are obtained. Then the features are fed as input to the proposed PSO based LLRBFNN model for classification and tumor detection.

This paper organised as follows: Section-II Presents the related work section –III Presents the Wavelet Transform, Support Vector Machine and feature extraction, Section–IV Presents proposed LLRBFNN Model with PSO training, Section-V Presents the results followed by conclusion and reference.

II. Related Work

Concretely, sundry approaches have been proposed to deal with the task of segmenting brain tumors in MR images, Such as automatic segmentation by the fuzzy algorithm can provide gratifying results even in cases where the boundaries of the ROIs cannot be facilely identified [4]. Predicated on the statistical information, the informative features extracted from the MR images. The right diagnosis at right time the medical image segmentation for detection of encephalon tumor from the magnetic resonance (MR) images is a very consequential process. Different classification methods have been proposed for relegation of encephalon tumors in MR images such as SVM, Multi-Layer Perceptron Network, PNN, Extreme learning machine etc. PNN Probabilistic Neural Network is found to be superior over other conventional neural networks such as Back propagation Neural Network in terms of its precision in relegating encephalon tumors.

Mohd Fauzi Bin Othman, Noramalina Bt Abdullah **[5]** in 2011, reported the performance of classification results of brain tumor using wavelet (Daubechies (db4)) and Support Vector Machine (SVM) and found accuracy of 65%. Mohd Fauzi Othman and Mohd Ariffanan Mohd Basri, 2011, [6], uses Principal Component Analysis and Probabilistic Neural Network (PNN) and reported precision of 73 to 100% with varying spread values from 1 to 3.Damodharan and Raghavan [7] have presented a precision of 83% utilizing neural network predicated classifier for encephalon tumor detection and relegation. Alfonse and Salem [8] have proposed SVM predicated classifier and expeditious Fourier transform (FFT) technique for automatic relegation of encephalon tumor from MR images and obtained a precision of 98.9%.

Zanaty [11] proposed a methodology for encephalon tumor segmentation predicated on a hybrid type of approach with FCM and obtained precision of 90% at the noise level. Torheim et al. [12], claimed better presages and ameliorated clinical factors, tumor volume, and tumor stage in comparison with first-order statistical features utilizing wavelet transform, and SVM's algorithm. Kumar and Vijayakumar [14] reported a relegation precision of 94% utilizing principal component analysis (PCA) and SVM.

Cui et al. [15] proposed a localized fuzzy clustering with spatial information and claimed precision between 83% to 95%.Wang et al. [16] have presented a medical image segmentation technique predicated on active contour model to deal with the quandary of intensity in homogeneities in image segmentation. Chaddad [17] has proposed Gaussian cumulation model (GMM) utilizing MR images for automatic feature extraction and PCA for the enhancement of the GMM feature extraction. Deepa and Arunadevi [18] reported a precision of 93.2%, the sensitivity of 91.6%, and specificity of 97.8% by proposing extreme learning machine for relegation of brain tumor from 3D MR images.

III. Methodology

A. *Research Workflow*

As divulge in the abstract, the features are extracted from the image by using wavelet transform and fed as input to the proposed PSO based LLRBFNN model for classification task. Also the features are given as input to the SVM and LMS based LLRBFNN Model for the validation of classification task results.

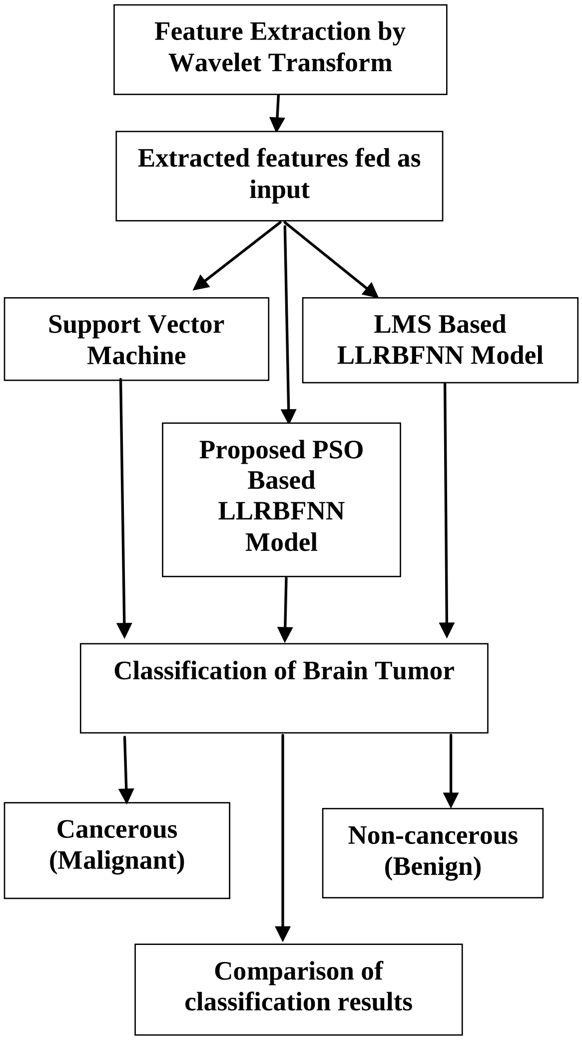

Figure: 1 Research flow diagram

B. ***Feature Extraction using Wavelet Transform***

Discrete Wavelet Transform is found to be an important tool in decomposing the images into different levels of resolution, from which the significant features can be extracted [29], [30].In this work Discrete Wavelet Transform (DWT) coefficients are used as feature vector. The wavelet transform has been used to extract features from the gray scale image such as Energy, Entropy, kurtosis, mean, standard deviation, smoothness, skewness and correlation. In the first instance the image has to be segmented to get the tumor region. But it is difficult to say, whether it is cancerous or non cancerous. The features will identify the variation and will be used for classification task. The wavelet transform is a popolar transform which has been used in the different areas of power signal processing,seismic signal processing, speech processing etc. Researchers also used wavelet transfrom as a feature extractor for the brain tumor detection[4].

The Discrete Wavelet Transform (DWT), provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time [21].There are two filters involved, one is the wavelet filter, and the other is the scaling filter. The wavelet filter is a high pass filter, while the scaling filter is a low pass filter. Filtering a signal corresponds to the mathematical operation of convolution of the signal with the impulse response of the filter. The continuous wavelet transform is given by

$$CWT_X^{\psi}(\tau,s) = \Psi_X^{\psi}(\tau,s) = \frac{1}{\sqrt{|s|}}\int x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \qquad (1)$$

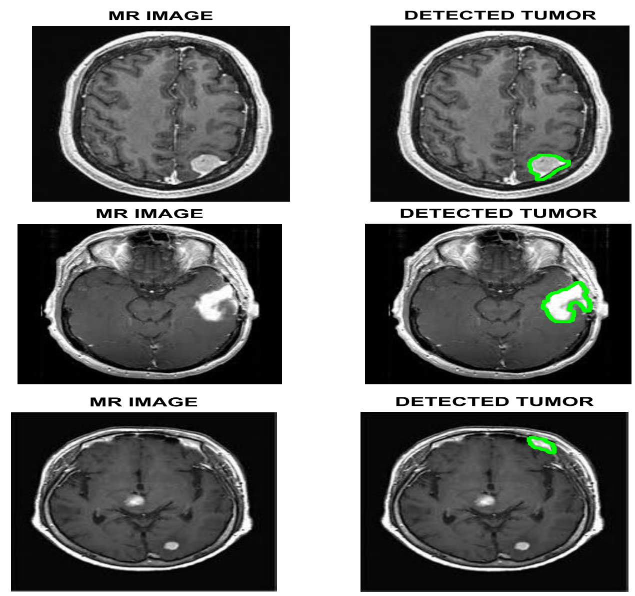

Figure 2. Detected Brain Tumor from MR Image

Table1: Feature Table

Features	Image 1	Image 2	Image3	Image4	Image 5
Mean	0.0019	0.0023	0.0063	0.0028	0.0019
Std. Dev	0.0897	0.0892	0.0893	0.0897	0.0894
Entropy	3.6549	3.9512	3.2016	3.6283	2.6652
Smoothness	0.8782	0.8731	0.9452	0.9132	0.8778
Kurtosis	5.8116	7.3123	8.2408	5.3238	7.2707
Skewness	0.3407	0.3215	1.1042	0.3229	0.6117
Correlation	0.1125	0.1225	0.1421	0.0957	0.1284
Energy	0.7553	0.7992	0.7862	0.7378	1.7491

In DWT Filtering a signal corresponds to the mathematical operation of convolution of the signal with the impulse response of the filter. DWT results in four sub bands LL (low low), LH (low-high), and HL (high-low), HH (high-high) at each scale. Sub band LL, is the approximation component of the image, and LH, HL, HH are the detailed components of the image along the horizontal, vertical and diagonal axis.

In this work Daubechies (db4) wavelet is considered for feature extraction purpose. Hence in this process, a four level decomposition has been computed. MRI datasets has been collected from the Harvard medical school architecture and Alzheimer's disease Neuroimaging Initiative (ADNI) public database (http://adni.loni.usc.edu/). A total of 200 MRI images of normal and abnormal images have been for training and testing. The input MRI images will undergo the process of gray image conversion, template creation, computation of correlation undergoes tumor location detection, brain tumor segmentation and training.

C. LLRBFNN Model with LMS training

In this model, it is noticed that in LLRBFNN [22] model a local linear model replaces the connection of weights between the hidden layer and output layer of conventional RBFNN. Also the input and number of hidden nodes are equal. In case of RBFNN [23] the input patterns or data coincide with that of the network weight or centers of the hidden nodes. In the LLRBFNN model, a random weight is trained iteratively and the local linear weight is given to the computational hidden node. This reduces the overall nodes required in the network and hence provides better approximation to the pattern classification task. The weights of the LLRBFNN Model is optimised with LMS algorithm.

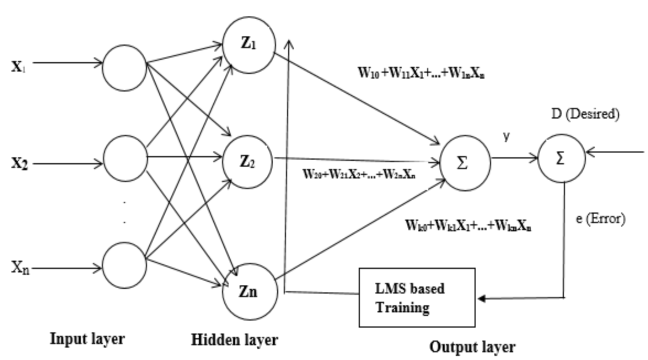

Figure 3. LLRBFNN Model with LMS Training

Where $x_1, x_2, \ldots\ldots x_n$ are inputs (features) and Z_1, Z_2, ------- Z_n are the Gaussian activation function in the hidden units.
The activation function of the n^{th} hidden neuron is defined by a Gaussian Kernel as

$$Z_n(x) = e^{\left(\frac{-\|x - C_n\|^2}{2\sigma_n^2}\right)} \quad (2)$$

Where σ_n^2 is the parameter for controlling the smoothness of the activation function and C_M is the center of the hidden node and $\|x - c_n\|$ indicates the Euclidean distance between the inputs and the function center.
The objective function is to minimize the error and the mean square error is given by

$$MSE(e) = \frac{1}{N}\sum_{n=1}^{N}(D_n - \theta_n)^2 \quad (3)$$

Where "D" is the desired vector.

In this network the weights are initialized to zero and optimized by using Widrow Hoff's Least Mean Square (LMS) algorithm [24]. In each learning cycle, the input pattern vectors are presented in a sequential manner, and the output vector is obtained.
The weight updation by LMS algorithm is given by

$$w(p+1) = w(p) + \eta(p)x_{kn}^T e_{kn} \quad (4)$$

For k = 1, 2, 3, ….. K, n = 1, 2, 3….. m = 1, 2, 3,…, M
The error is calculated by subtracting the actual output from the desired output vector:

D. LLRBFNN Model with PSO training

In this model the PSO (Particle Swarm Optimization has been employed for the weight optimization. PSO [25] is a population based stochastic optimization technique inspired by social behavior of bird flocking. A concept for optimizing nonlinear functions using particle swarm methodology. PSO uses a population of individuals, to search feasible region of the function space. In this context, each candidate solution is called particle and represents one individual of a population (features).The population is set of vectors and is called swarm (set of feature data points). The particles change their components and move (fly) in a search space.
The velocity update equation is given by

$$v_i(t+1) = wv_i(t) + c_1r_1(pbest(t) - x_i(t)) + c_2r_2(gbest(t) - x_i(t)) \quad (5)$$

And the position update equation is given by

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (6)$$

Learning factors c1and c2usually equal to 2 taken in this research work. The maximum number of 1000 iterations are considered to execute and for the minimum error requirement by PSO algorithm

The PSO Process follows as:
1. Initializing particles with random position and velocity vectors.
2. In the next phase evaluate *fitness f*or each particle's position (p).
3. If fitness (p) better than fitness (pbest) then *pbest*= p.
3. Then set best of *pbests* as *gbest* and Update particles velocity and position

5. Stopping criteria: giving *gbest*, optimal solution.
6. If not, Go to step 2, and repeat until convergence or a Stopping condition is satisfied.

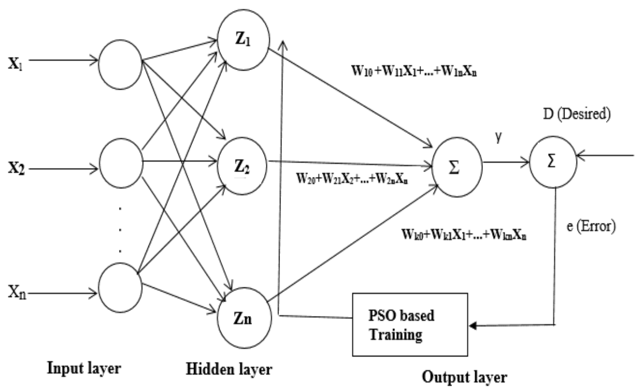

Figure 4. LLRBFNN Model with PSO training

IV. RESULTS AND DISCUSSION

We have extracted the feature and tested with the LMS based LLRBFNN model and PSO based LLRBFNN model

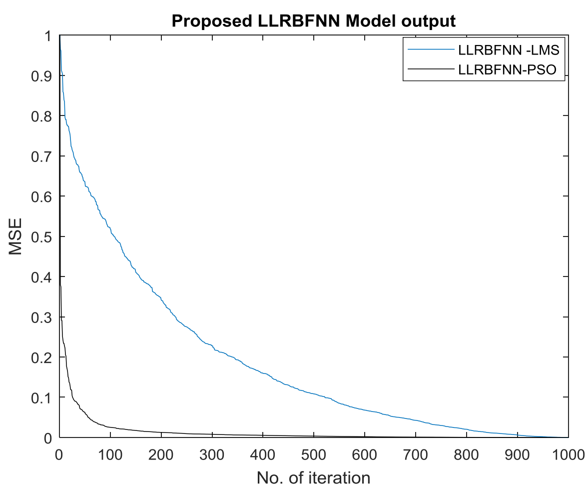

Figure 5. Mean square error using LLRBFNN Model

Out of 200 images 150 images has been taken for training and the rest 50 images taken for testing. It is found from the result that the model LLRBFNN with LMS training has taken near about 800 step to optimize where as the model LLRBFNN with PSO training taken near about 200 iterations for optimization. It also found that the computational time is taken by LLRBFNN with LMS 17.453676 sec and LLRBFNN with PSO training take 9.213453 sec. The results have been obtained from the model and percentage accuracy, computational time has been calculated using MATLAB R2017a software.

Table-2: Percentage Accuracy of the model

Model	No. of data	Computatio nal time	Percentage accuracy
LLRBFNN -LMS	**2000**	**17.453676**	**95.3**
LLRBFNN -PSO	**2000**	**9.213453**	**98.7**
SVM	**2000**	**22.345234**	**91.7**
RBFNN-LMS	**2000**	**19.216236**	**83.5**
RBFNN-PSO	**2000**	**18.873592**	**89.2**

V. CONCLUSION

The research work aim is to accomplish a better precision results in considering the two types of tumors through a coalescence of different machine learning techniques for classification, feature extraction and image segmentation. The proposed model has the potentiality of relegating the tumor and will avail clinical diagnosis. The manual detection of brain tumor is a complex and difficult task by the radiologists. The automatic detection and classification using the proposed LLRBFNN model with LMS and PSO training is the main focus of the paper. In the first stage the images are segmented and features are extracted using wavelet transform. There are eight features have been considered for the classification task. The proposed model LLRBFNN with PSO and LMS training has been employed for the classification and the results were compared with the conventional SVM approach. From the result it is found that the proposed model provides better classification accuracy and less computations time as compared to other conventional methods.

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