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An Efficient Distributed Brain Image Classification via Particle Swarm Optimization and Support Vector Machine

K.Mageswari, Dr.R.Renuga

Abstract— Automated abnormal brain identification is of major importance for clinical diagnosis. Processing of Magnetic Resonance Imaging (MRI) is an important task in brain image classification. This work using image processing is a time consuming process. So, the proposed system adapted distributed computing concept. Features like Skew, Kurtosis, Fourier shape and Haralick texture is extracted by the distribution system based on Round robin scheduling followed by preprocessing. In this proposed technique, feature selection is done using Particle Swarm Optimization(PSO) and feature classification using Support Vector Machine(SVM).By making use of these classification, diseases like glioma, metastatic adenocarcinoma, cerebral calcinosis, carcinoma, meningioma, sarcoma, etc., from the abnormal brain images are identified efficiently**.**

Index Terms—Feature extraction, Load balancing, Magnetic Resonance Imaging (MRI), Support vector machine (SVM), Task distribution

1 INTRODUCTION

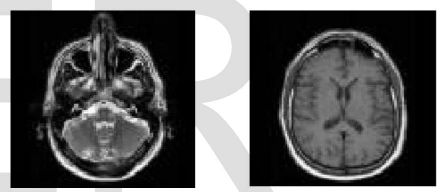
Human brain is considered as a major part of a body and it has a complex structure. Every function of a human body is governed by a brain. Brain acts a kernel part of the body and thus to diagnosis of the tumor or any abnormality is very important now-a-days. Magnetic Resonance Imaging (MRI) is one of the medical imaging techniques which visualize the internal structure of the brain**.** Magnetic resonance imaging of brain image computing has been increased in the field of medicine by providing some dissimilar methods to extract and visualize information from medical data, obtained using various acquisition modalities. Brain disease classification is a significant process to extract information from complex MRI of brain images. Diagnostic imaging is a vital tool in today's medical field.

Magnetic resonance imaging (MRI): MRI Scanner or MRI is a powerful magnet to polarize and excite hydrogen nuclei that is proton in water molecules in the human tissue that produces a detectable signal which is spatially encoded, resulting in images of the body. It mainly uses three electromagnetic fields they are:

1. A strong static magnetic field known as static field is used to polarize the hydrogen nuclei,
2. A weaker time varying field(s) known as gradient field for spatial encoding
3. To produce measurable signals collected through RF antenna, a weak radio frequency field for manipulation of hydrogen nuclei is utilized

- K.Mageswari is currently pursuing masters degree program in computer science and engineering in Coimbatore Institiute od Technology, Coimbatore, India. E-mail: magesk17@gmail.com
- Dr.R.Renuga working as Associate Professor in department of computer science and engineering in Coimbatore Institute of Technology, Coimbatore, India. E-mail: renugacit@yahoo.co.in

The changeable actions of protons within different tissues lead to differences in the appearance of tissue. The different positioning of MRI of the brain is shown below.



(a) (b)

Fig. 1(a) head shows maxillary sinus, nasal septum, clivus, inner ear, medulla, and cerebellum, Fig. 1(b) brain shows cortex, white and grey matter, third and lateral venticles, putamen, frontal sinus and superior sagittal sinus.

The major advantage of MRI is its non-invasive technique.Diagnostic values of MRI are considerably exaggerated by the precise and automatic categorization of the MR images

Several feature selection and classification techniques are used earlier as follows. Cocosco, Zijdenbos and Evans [1] shows the supervised classification that includes nearest neighbors (k-NN) and another method is on unsupervised classification, including self organizing feature map (SOFM) [2] and fuzzy -means [3]. While all these techniques attain fine results, yet the supervised classifier performs superior than unsupervised classifier in conditions of classification accuracy [4]. EminTagluk.Akin and Sezgin[5] shows that the wavelet transform is an proficient tool for feature withdrawal from MR brain images, because they allow study of images at different levels of resolution due to its multi decision analytic property, but it still remains to be an disadvantage as it needs huge storage and computationally expensive.

Selvanayaki and Kalugasalam[6] shows, Brain tumor image segmentation is done using metaheuristic algorithm such as Ant Colony optimization (ACO), genetic algorithm (GA) and Particle swarm optimization (PSO) for segmenting brain

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tumors in 3D magnetic resonance images. The pre-processing phase is completed by using tracking algorithms. Then the processed MRI image is segmented using ACO, GA and PSO and thus provides better segmentation result of tumor from brain MRI. Thus PSO algorithm performed better than ACO and GA algorithm for tumor detection and detection.

Mehdi Jafari, RezaShafaghi [7] shows that an automated classification method to classify normal and abnormal images using SVM classifier is presented. Features such as PCA and GLCM are classified by using SVM classifier. Thus maximum accuracy is not achieved by using feature of PCA. Additionally it results in producing classified result by utilizing high computational time.

Overcoming the above drawbacks, the proposed system uses PSO for feature selection and SVM for classification after the task distribution is completed. Among the supervised classification methods, the SVM is best at machine learning theory when compared with other methods such as decision tree [9], Bayesian and artificial neural networks.

2 PROPOSED METHODOLOGY

The proposed system contains stages such as preprocessing using median filter, Distributed feature extraction-Skewness, Kurtosis, GLCM texture values, Haralick shape, feature selection, classification. Stages of the proposed system is described below in detail as follows,

2.1 Preprocessing

Pre-processing is primarily done prior to the study of the main goal and extraction of the desired information which normally does the geometric corrections of the original actual unwanted atmospheric noise, removal of non-brain element image in the original image. In this, the input image can be preprocessed by using median filter. Median filter in MRI Images removes the noise with high frequency components. This calculates the median values that are finding the set of median of pixel value of the surrounding pixels to calculate the new denoised pixel value.

$$F(x,y)= \underset{(i,j)\text{belongs to } N}{median} \{g(i,j)\} \quad (1)$$

The median is estimated by sorting all pixel value by their sizes. Then selecting the median value as the new value for the pixel is made. The fundamental operation of the median filter as given in (1) where f (x, y) is the output median and g (x, y) is the original values.

2.2 Feature Extraction

Feature extraction is the recognition of the uniqueness of an object of interest in an image. The suitable selection of this unique property is the key to the success of much recognition and analysis tasks.The features of Skewness, kurtosis, Fourier shape [8] and Haralick feature can be extracted by using distributed system. The task can be distributed in parallel by Round Robin fashion.Features extracted by the nodes interconnected are given in below,

(1)Skewness: Skewness is a measure of intensity based feature which is defined as a measure of symmetry of the probability distribution of a real valued random variable as given in (2),

$$\mu^3=\sigma^{-3} \sum_{i=0}^{N_g-1} (i-\mu)^3 p(i) \quad (2)$$

$\mu^3<0$ Histogram below mean, $\mu^3=0$ Histogram is equal to mean, $\mu^3>0$ Histogram above mean

where μ is the mean that defines the average level of intensity of image, N_g is the total number of gray levels in the entire image and p (i) is the probability density

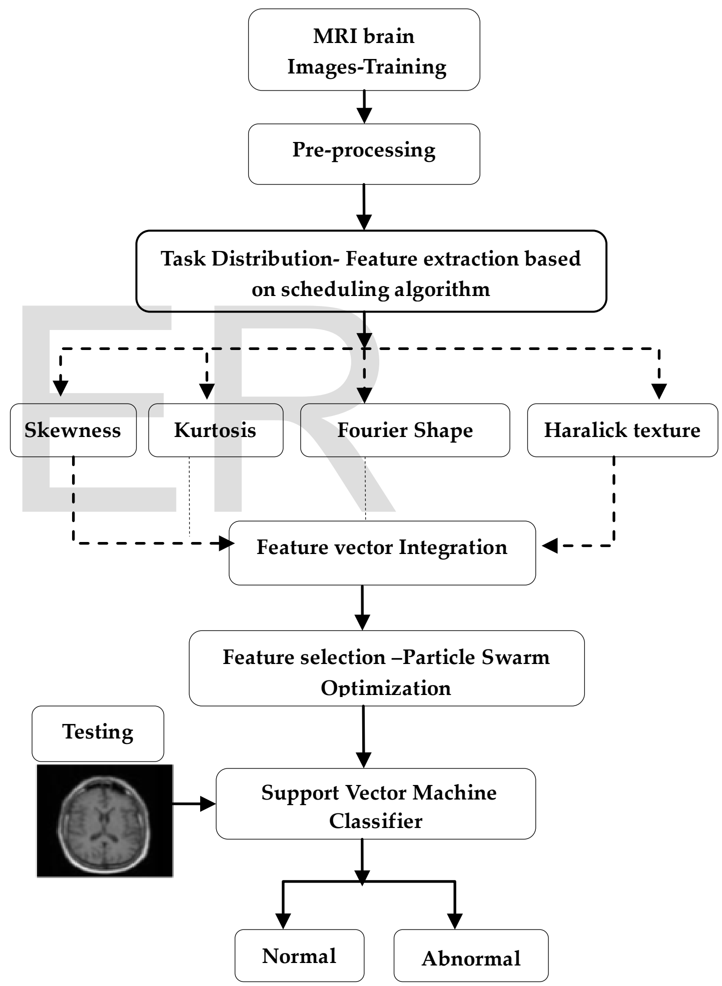

Fig.2 shows the architectural diagram of the proposed system

(2)Kurtosis: Kurtosis is a measure of the intensity based feature which is defined as a measure of the flatness of the histogram. And it is a measure of how outlier level a distribution is made as shown in (3),

$$\mu^3=\sigma^{-4} \sum_{i=0}^{N_g-1} ((i-\mu)^4 p(i)) - 3 \quad (3)$$

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where μ is the mean that defines the average level of intensity of image, N_g is the total number of gray levels in the entire image and p (i) is the probability density

(3)Haralick texture:Haralick texture features derived from GLCMs (Gray level co-occurrence matrix) are employed to extract low- and high-frequency by depending on the distance from each other of pixels used in the co-occurrence matrix of texture-like properties Then the mean and the range of these features can be computed, which constitutes features per image for a known interpixeldistance.GLCM features such as angular second moment, contrast, inverse difference moment, entropy, correlation and sum of variance has been extracted.[7]

(4)Fourier shape descriptor: The Fourier transform of each shape signatures of MRI image can be extracted as follows:

$$FSD(k) = 1/n \sum_{i=0}^{n-1} s(i) \exp(-j2\pi ki/n), \quad k=0, 1....n-1 \qquad (4)$$

where s(i), i = 0, 1, . . . , n − 1, is a shape signature at the i th point,j=√-1 .The coefficients FSD (k), k = 0, 1. . . n-1, are called Fourier descriptors of the shape of a MRI brain image.

These features can be extracted by inputting the image into the distributed system and then integrated by vector method. The step by step of the extraction process using Round robin fashion is shown in the following pseudo-code

```
Input: Number of nodes N, number of iterations K, Image I^K
For k=1 to K do
        For each of N nodes i, in parallel do
        Schedule task T based on the Round Robin to nodes N
        Extract features of Skew S(k)_i, Kurtosis KS(k)_i, Fourier Shape FS(k)_i, and Haralick H(k)_I
        Send average delay, Throughput of N nodes to master node
        End for
The master node updates I^K to I^{K+1}
The master node broadcasts I^{K+1} to all the other nodes.
End for
```


2.3 Feature Selection

For classification purposes, this extracted feature can be selected. Since these features are redundant, little value can be added for classification. So selection of these features can be done. The optimal feature can be selected by using Particle swarm optimization. The PSO is a populated global optimization method, deriving from the group of bird flicking research. It is simple and rapid to implement.

PSO makes searching via a swarm of particles which is updated from iteration to iteration. To search for the optimal solution, each particle moves in the direction of its previous best position (p_{best}) and the best global position in the swarm (g_{best}) as follows in (5),

$$
\begin{aligned}
&P_{best\,(i)} = P_i(k^*)\\
&Fitness\ (P_i\ (k^*)) = \min_{k=1....t} [fitness\ (P_i\ (k))]\\
&g_{best\,(i)} = P_{i^*}(k^*)\\
&Fitness\ (P_{i^*}(k^*)) = \min_{k=1....t,\ i=1....P} [fitness\ (P_i\ (k))]
\end{aligned} \qquad (5)
$$

where i denotes particle index, P denotes total number of particles, t denotes current iteration number, k denotes the iteration index and p denotes the position. The position (p) and velocity (v) of particle is updated as follows in (6),

$$
\begin{aligned}
&p_i(t+1) = p_i(t) + v_i(t+1)\\
&v_i(t+1) = wv_i(t) + c_1 r_1 (p_{best(i)}(t) - p_i(t)) + c_2 r_2 (g_{best(t)}(t) = p_i(t))
\end{aligned} \qquad (6)
$$

where w is the inertia weight to balance the global and local values,c_1 and c_2 are positive constant parameters,r_1 and r_2 denotes the random variables of uniform distribution within the range of (0,1)

2.4 Classification

Support Vector Machine (SVM) is a dominant supervised classifier and it shows better accuracy and computational advantages over some other conventional classification approaches. This classifier is based on the structural risk minimization principle from the statistical learning theory. In this the selected feature vector such as Skewness, Kurtosis, Fourier shape, and Haralick texture features is trained by using the Support Vector machine. For a given class in high dimensional feature space, SVM searches an optimal separating hyperplane between members and non –members. The inputs to the SVM algorithm are the feature subset selected using PSO. In this method two classes such as normal and abnormal of the brain image has been classified. Then classification procedure divides the abnormal brain into brain diseases such as glioma, metastatic adenocarcinoma, motor neuron disease, cerebral calcinosis, carcinoma, meningioma, sarcoma, etc., SVM classifier takes N training samples and trains N-1 samples. Then remaining one sample is used for testing purpose. This process is repeated until all N samples have been used as a test sample. The performance of the classification is evaluated by estimating accuracy.

3 EXPERIMENTAL ANALYSIS

The experimental analysis were done using MATLAB 7.10 R2010a and above (theMath Works). The datasets of 68 MR brain images were downloaded from the Harvard Medical School,*(URL:http://www.med.harvardedu/aanlib/home.html)*
The Brain MR images that are abnormal of the datasets contain the following diseases: Glioma, Metastatic adenocarcinoma, cerebral calcinosis, Meningioma, Sarcoma etc.

Processing of MRI on a single machine consumes higher time for feature extraction process, (850 seconds for 68 MRI samples 68 * 4 = 272 extracted feature values) but here the proposed method of distributed computing reduces it to 300 seconds.Classification using PSO + SVM yields 94% ,which proves to be efficient than the existing method which uses Genetic + Decision tree algorithm.

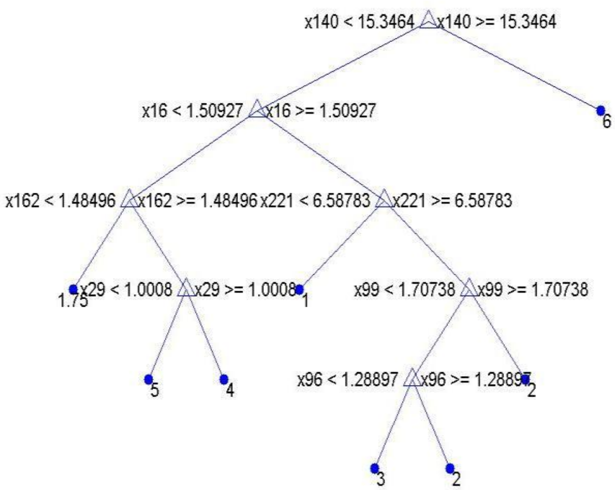

Fig .3 Generated Regression Tree during the classification of MRI brain images

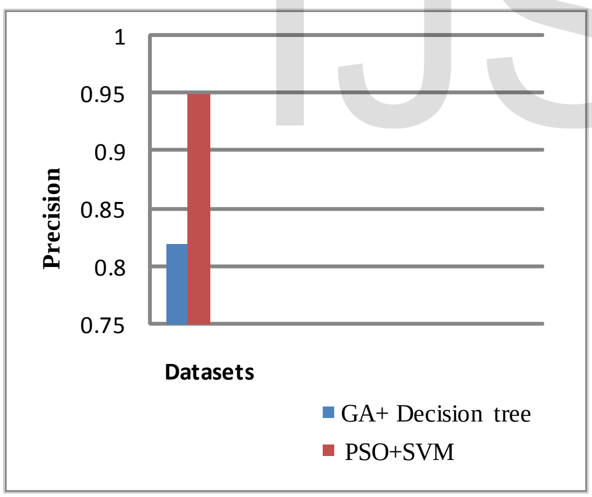

Fig. 4 Precision Graph

Fig. 4 shows the precision graph comparing Genetic and Decision tree algorithm with the proposed system Particle swarm optimization and SVM classifier

Fig. 5 shows a better Classification accuracy with proposed system -Particle swarm optimization and SVM classifier when comparing with the Genetic and Decision tree algorithm

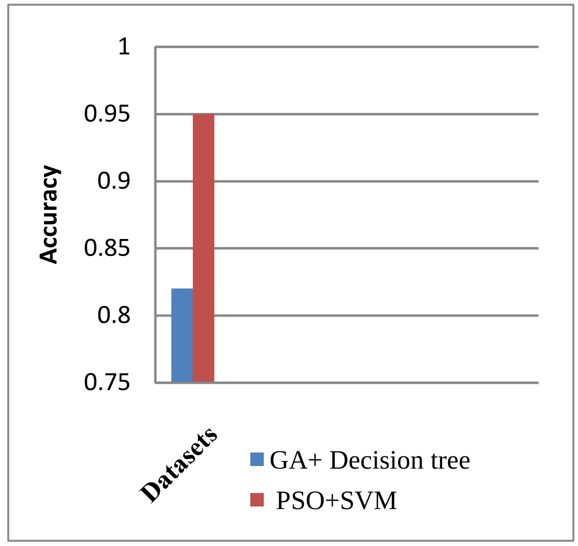

Fig.5 Classification Accuracy Graph

4 CONCLUSION

In this proposed work, automatic classification of brain image has been done using distributed mechanism of feature extraction .MRI Image is preprocessed by using median filter. Then post processing of feature Extraction has been done by using distributed mechanism .Features such as Skew, Kurtosis, Fourier shape and Haralick texture feature has been extracted in distributed environment based on Round Robin scheduling. Then optimal feature vectors of extracted feature can be selected by using Particle swarm optimization (PSO).This optimization method yields best features for classification process. With these features an efficient classifier known as Support vector Machine has been trained. This classifier efficiently classifies the normal and abnormal image of brain and further shows the different diseases namely glioma, metastatic adenocarcinoma, motor neuron disease, cerebral calcinosis, carcinoma, meningioma, sarcoma, etc from the abnormal image. Experimental result provides better classification accuracy and reduced time complexity for extracting features when compare with the existing work.

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