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Hybrid Swarm Intelligence Based FA with Modified Levenberg Marquardt Classifier for Detection of Brain Tumors Through Brain MRI Images

[1]A. Shenbagarajan, [1]V. Ramalingam, [2]C. Balasubramanian and [1]S. Palanivel
[1]Department of Computer Science and Engineering, Annamalai University, Chidambaram
[2]Department of Computer Science and Engineering,
PSR Rengasamy College of Engineering for Women, Sivakasi, Tamil Nadu, India

Abstract: Most commonly occurring causable disease among human beings is the Brain Tumor, subsequently early discover of brain tumor is important. In order to get over discover an issues of tumor from brain employing MRI images, an efficient classification method for classifying the brain MRI as Tumourous and non-Tumourous classes by making use of hybrid classifier is proposed. There are three critical early stages of brain MRI image analysis prior to the classification process. In the first step is the preprocessing stage which uses the Adaptive Median Filtering (AMF) method for noise elimination from brain MRI, then follows the segmentation process on these enhanced images on the basis of the regions of the images making use of Active contour Model (ACM) with extracted surface feature. The surface feature extraction is done by employing Kernelised Fuzzy-C-Means (KFCM), later from these segmented images, two most vital features are extracted based on the image edges, which are texture and shape. Texture features and shape features are extracted by utilizing hybrid wavelet transform and Sobel, Canny methods. Then, the most significant feature for classification process is chosen using Principal Component Analysis (PCA), finally, hybrid Firefly Algorithm-Modified Levenberg Marquardt (FAMLM) classifier used for classification. The experimental results of this proposed technique demonstrates that the efficiency of the hybrid classifier outperforms than that of the existing classifier.

Key words: Magnetic Resonance Imaging (MRI), hybrid classifier, Adaptive Median Filtering Method (AMF), Active Contour Model (ACM), Kernelised Fuzzy-C-Means (KFCM), Firefly Algorithm-Modified Levenberg Marquardt (FAMLM) classifier

INTRODUCTION

The human brain tumor diagnosis and treatment is currently dependent on clinical symptoms and the radiological appearance through Magnetic Resonance Imaging (MRI). Nonetheless, treatment response of brain tumor varies according to the tumor stages. Modern day technologies may greatly enhance earlier tumor diagnosis and may permit individuals to make the most efficient usage of treatments in brain tumors. Magnetic resonance imaging is a technique that reveals information about the human body, particularly the most important human organ which is the brain. This MR imaging technique has been shown to considerably improve the accuracy of tumour diagnosis. But, MR imaging processes are sophisticated and expertise is necessary for its understanding. Here, this researcher is focused on the segmentation, feature extraction techniques which is used for making the analysis easier and hence, allows a faster classification of MRI data.

In the recent times, several classification techniques have been evolved for brain MRI image analysis for the cause of tumor diagnosis. Here, this proposed reseach describes the most efficient techniques along with classification process for tumor diagnosis obtained from the brain MRI images.

Removal of noises from the image is an early stage in the image processing which improves the images for further proceedings, since noises in images results in the errors such as blurring effects. Different filtering algorithms have been introduced in the literatures (Alajlan and Jernigan, 2004) for elimination of noises. Adaptive Median Filter (AMF) is exploited extensively in order to eliminate noise in practice. For improvement over the blurring effects, this proposed researcher makes use of the AMF for the purpose of achieving a balance between straightforward averaging and all-pass filtering. The proposed AMF outperforms rather than the other filters, and usually eliminates noises whilst preserving the edges of the images used in MRI image processing.

Corresponding Author: A. Shenbagarajan, Department of Computer Science and Engineering, Annamalai University, Chidambaram, Tamil Nadu, India

Medical images are usually with ambiguity. In case, the objects of interest and their boundaries can be located precisely, meaningful visual information would be given to the physicians, making the subsequent examination much easier. Among the various image segmentation algorithms, ACM is extensively utilized with its clear curve for the object. Based on the energy, there are two important categories of ACM segmentation: edge-based models (Bresson *et al*., 2007; Hahn and Lee, 2010; Zhu *et al*., 2007) and region based models (He *et al*., 2012; Liu *et al*., 2013; Liu *et al*., 2010). Edge-based ACM depends on the image gradient to halt the evolving contours on the object boundaries desired. In the case of images with weak boundaries, the energy functional of the edge-based ACMs will hardly near zero along the boundaries of the objects and the evolving curve might pass through the real boundaries. Hence, the edge-based ACM always fails in segmenting the medical images properly, since blur or weak edge generally occurs in the medical images, particularly in MRI brain images which usually contains large area of blur boundaries between gray matter and white matter. When compared with the edge-based ACM, the region-based ACM do not make use of the image gradient, they employ image statistics inside and outside the contours in order to control the evolution with better performance or images with weak edges or without edges. Therefore this proposed work uses region based ACM for image segmentation. Still, this segmentation process will impact the leakage of boundaries of the MRI images that can be decreased by applying the Kernelised Fuzzy C Mean algorithm (KFCM), that will prevent the edges of images by extraction of surface features from the image on the basis of their edges. Edges of brain MRI image can be detected when changes in local surface characteristics (surface normal, gradients, principal curvatures) go beyond a pre-set threshold. This procedure is followed by categorizing the points inside the boundaries and result in the segmented regions employing ACM.

After the segmentation of MRI images, features such as texture and shape are vital for classification process. The texture analysis has a significant role to play in the characterization of MRI images. Texture analysis techniques can be classified as statistical, geometrical, and signal processing types (Li and Meng, 2009). The Wavelet-Transform Family methods are typical instances of multi-resolution texture analysis techniques. The most generally employed wavelet transform in MRI image processing is the Discrete Wavelet Transform (DWT) (Li and Meng, 2009) whose discrete time shifting and stretching variables result in a sparse and effective representation. The DWT takes an input image and decomposes it into four sub image components which characterize it for various orientations in the horizontal and vertical frequency axes. Attempting to express the directional features in a more efficient manner, many directional wavelet systems have been presented in (Do and Vetterli, 2005; Ferrari *et al*., 2001; Cui and Zhang, 2010; Geback and Koumoutsakos, 2009). DWT produces the sub bands, these generated sub bands are utilized in the Modulated Cosine Wavelet Transforms (MCWT) is used to normalize the extracted texture features from the original segmented MRI image. The shape representation of the MRI image is also considered as one of the essential image discrimination factors in image processing. Shape representation can be chiefly of two types: boundary based or region based. Only the outer boundary of the shape is brought into use in boundary based shape representation. In order to get the entire boundary of the shape in the image in the form of connected edges, slope magnitude method is used along with gradient operators. This proposed researcher introduces the shape feature extraction relying on the shape content as edges that are observed in the image that are extracted exploiting Sobel and Canny edge detection techniques (Kekre *et al*., 2010).

From these extracted feature vector and values, the most important feature components are chosen by making use of the Principal Component Analysis (PCA) and then on the basis of the choice of these significant features, the MRI images are classified applying hybrid classifier in the proposed system. Prior to the classification these extracted features are optimized making use of Firefly algorithm. Different optimization techniques have been hybridized in order to acquire the best features of each whilst eliminating the computational cost. This proposed work has recently reported a preliminary effort (Abdullah *et al*., 2012) in order to hybridize the Firefly Algorithm (FA) (Yang, 2009) along with the artificial neural network based Modified Levenberg Marquardt (MLM) for training operations of the MLM. Among these techniques, evolutionary computation was observed to improve classification accuracy and thereby reduce computation time. The final results indicate that the proposed techniques are capable of classifying between various abnormal and normal classes of the brain MRI image and hence provide better classification accuracy in comparison with the other existing techniques. The following sections describe the brain MRI image analysis techniques proposed in detail.

Literature review: In a new method Cuckoo Search Levenberg Marquardt algorithm is introduced by merging the best features of two known algorithms

Back-Propagation (BP) and Levenberg Marquardt local minima problem through training this net Algorithm (LM) for enhancing the convergence speed of ANN training and preventing work. Few chosen benchmark classification datasets are utilized for simulation.

Zhang *et al*. (2011) is proposed a novel classification technique based on Neural Network (NN) which classifies a given MR brain image to be tumourous or non-tumourous. This method is initially focused on wavelet transform for extraction of features from images and then the technique of Principle Component Analysis (PCA) is applied for dimensionality reduction of the features. The reduced features are then processed by making use of a Back Propagation (BP) NN, with which Scaled Conjugate Gradient (SCG) is utilized to compute the optimal weights of the NN.

Najafi, etc., presented the diagnosis techniques, which has four stages, namely preprocessing, feature extraction, dimensionality reduction and classification. In the first stage, histogram equalization of image is performed, then the necessary vital features are extracted on the basis of Discrete Wavelet Transformation (DWT). Then the extracted features are reduced exploiting Principal Component Analysis (PCA). Finally, classification is performed by using three methods like K-Nearest Neighbor (K-NN), Parzen Window and Artificial Neural Network (ANN).

Rajalakshmi and Prabha (2015) presented the magnetic resonance brain image classification that is based on a modern Computer-Aided Diagnosis (CAD) technique. This present technique implements color converted hybrid clustering segmentation algorithm with hybrid feature selection approach which is based on Information gain and Sequential Forward Floating Search (IGSFFS) and Multi-Class Support Vector Machine (MC-SVM) classifier technique for separating the MR brain images into three group comprising of normal, benign and malignant. This hybrid segmentation algorithm that is the combination of WFF (Weighted Firefly) and K-means algorithm referred to as WFF-K-means and modified Cuckoo Search (MCS) and K-means algorithm known as MCS-K-means which can find better cluster partition in brain tumor datasets and also get over local optima issues in K-means clustering algorithm. The results indicated in this proposed method yields the better performance in comparison to other algorithms such as PSO-K-means color converted K-means, FCM and other conventional approaches. The multiple feature set contain color, texture and shape features that are derived from the segmented image. These features are then given into a MC-SVM classifier provided with hybrid feature selection algorithm, trained with data that is labeled by experts, thus helping in the detection of brain images with high accuracy levels.

In this researcher, Hussain *et al*. (2012) formulated a novel scheme for the purpose of accurate segmenting the normal and pathological tissues in the MRI brain images. This scheme primarily carries out a classification process by means of utilizing Fuzzy Inference System (FIS) and Feed Forward Back Propagation Neural Network (FFBNN). These two classifiers are making use of the image features which are extracted for the classification process. The features are extracted through two manners. There are five features were extracted from the MRI images: they are two dynamic statistical features and three 2D wavelet decomposition features. During the Segmentation process, the normal tissues and pathological tissues are segmented from the MRI. The unnecessary tissues in the non-tumourous images are eliminated during the stage of preprocessing.

The discussed MRI brain image analysis scheme for the purpose of tumour diagnosis process, most essential classification and segmentation results are analyzed. A metaheuristic cuckoo search scheme with ANN based LM algorithm given in for efficient classification outcomes using different benchmark datasets. Zhang *et al*. (2011) and Najafi investigated regarding the neural network based classifiers that can enhance the quality of medicinal preparation in tumour diagnostic tasks. While considering (Rajalakshmi and Prabha, 2015) it uses the hybrid classification methods for the precise classification results and while by Hussain *et al*. (2012) utilized the fuzzy based neural network schemes for image MRI segmentation. Based on all these aforementioned schemes, it is observed that some major issues in feature extraction, segmentation and classification are done with certain drawbacks during the process of tumor diagnosis in MRI data.

Therefore, in order to overcome the drawbacks of high computational complexity, low computational speed and high costs, a surface features extraction with robust region based segmentation, texture and shape feature extraction for effective classification and hybrid swarm intelligence optimization FA approach with ANN based LM classifier is proposed in this research.

MATERIALS AND METHODS

The major objective of this proposed method is to design and develop an approach for the purpose of tumour diagnosis using brain MRI image classification with feature extraction and segmentation. There are several schemes that find a tumour in brain MRI images

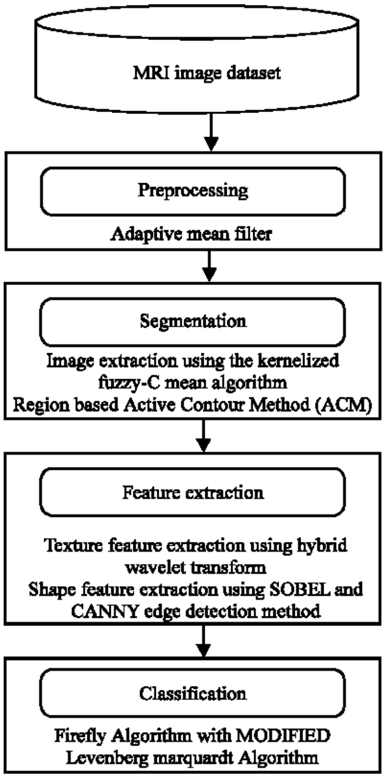

Fig. 1: Overall strucural diagram for proposed methodology

automatically. With the aim of achieving promising results with MRI brain tumour classification have planned to make use of region based ACM and hybrid classifier (FAMLM). In the proposed approach, during the process of detection of tumour the following steps are involved, pre-processing, segmentation, feature extraction, feature selection and tumor classification process. In the beginning, the MRI image is pre-processed for the purpose of effective segmentation and de-noising process will be done with the assistance of the non-linear smoothing filters such as Adaptive Median Filter (AMF). After that, the pre-processed image is segmented in accordance with segmentation techniques and the features are extracted from the each segment. After the segmentation, the edge preserving surface features are extracted from the MRI. At this point, a region based ACM will be developed for the purpose of extracting the tumour part. After that, the texture and shape based features will be extracted with the segmented regions. Once the feature extraction is done, the most important features are selected with the assistance of PCA, then the selected features are utilized for classification process, the classification will be done with the assistance of hybrid classifier. In the hybrid classifier, FA algorithm will be utilized with Modified Levenberg-Marquardt Training algorithm in neural network. At last, several brain MRI images are subjected to the proposed technique to assess the performance in classifying the tumourous or non-tumourous from the brain MRI. Here, for experimentation, the DioCom MRI Image dataset will be subjected to analyze the performance of the proposed approach utilizing accuracy, sensitivity and specificity. Figure 1 depicts the block diagram of MRI brain image analysis process's proposed methodology.

Preprocessing for Brain MRI images: The aim of the preprocessing stage in proposed brain MRI image process is to removing low-frequency background noise and enhancing the MRI images. An image preprocessing is one of the most important techniques of enhancing images prior to computational processing. Here, this proposed method used a nonlinear filtering method that is an Adaptive Median Filter (AMF) (Thivakaran and Chandrasekaran, 2010) to reduce impulsive-like noise, resulting the preprocessing method used AMF, in a maximum preservation of the original information of given MRI input image. Basically, the MRI images doesn't have much background noises, for best classification results for brain tumour analysis, in this study, proposed a filtering scheme to remove unwanted things such as impulse noise from images such that the scheme should work more efficiently and should perform superior to the existing schemes in terms of noise rejection and preservation of original image properties.

Adaptive median filtering method: AMF method has been usually applied for the purpose of removal of noises from images in image processing. This scheme is an advanced method compared with standard median filtering to elimination of unwanted things from the MRI images. The major process AMF in the preprocessing stage is as follows: Get rid of impulse noise from the input image; smoothing of remaining noises and considerably lessen distortion, like extreme thinning or thickening of object boundaries. The following study describes regarding the function of AMF in removal of noises from the MRI images.

Noise removal using adaptive median filter: AMF carries out spatial processing for the purpose of determining which pixels in an image have been influenced by impulse noise. AMF classifies pixels as noise by comparing each pixel in the image to its nearby neighbor pixels. The size of the neighborhood is modifiable, in addition the threshold for the purpose of comparison. A pixel that is different from a majority of its neighbors, moreover it is not structurally aligned with those pixels to which it is similar, is regarded as impulse noise. These noise pixels are subsequently replaced by the median pixel value of the pixels in the neighborhood that have passed the noise labeling assessment. AMF transforms size, $Size_{a,b}$ (the size of the neighborhood pixel) at some stage in the filtering operation.

AMF notations are described as given below. The input dataset image is regarded as IMG, here IMG_{min} indicates the minimum gray level value in changes size of $Size_{a,b}$, IMG_{Max} maximum gray level value in changes size of $Size_{a,b}$, $IMG_{a,b}$ = Median of gray levels in changes size of $Size_{Max}$ = Gray level at coordinates (a, b), $size_{max}$ = Maximum allowed size of changes size of $Size_{a,b}$ (Algorithm A).

Algorithm A; Used for adaptive median filtering process:

LEVEL-I:
STEP 1: IF IMG_{min}<IMG_{med}<IMG_{max} then
IMG_{med} is not an impulse
go to LEVEL-II to test if $IMG_{a,b}$ is an impulse...
ELSE,
IMG_{med} is an impulse
STEP 2: the size of the window is increased and
STEP 3: LEVEL-I is repeated until...
(a) IMG_{med} is not an impulse and go to LEVEL-II or
(b)IMG_{max} reached: output is
LEVEL-II:
STEP 4: IF IMG_{min}< $IMG_{a,b}$< IMG_{max} then
$IMG_{a,b}$ is not an impulse
STEP 5: OUTPUT is (distortion reduced)
ELSE
either $IMG_{a,b}$ =IMG_{min} or $IMG_{a,b}$= IMG_{max}
STEP 6: OUTPUT is IMG_{med} (standard median filter)
IMG_{med} is not an impulse (from LEVEL-I)

The AMF scheme can handle impulse noise from the MRI images more effectively. Further, advantage of the AM filer is that it looks to preserve information at the same time removing non-impulse noises from the images. The adaptive algorithm performed well in a high level noise input MRI image data.

Brain MRI image segmentation: Image segmentation is a kind of process that intends to partition an input MRI image into a set of semantically meaningful, homogeneous and non-overlapping regions of related attributes like intensity, depth or texture. The result of segmentation process is a set of contours which portray the region boundaries. Image analysis comprises the classification of MRI data into particular tissue categories and the recognition and description of precise anatomical structures.

MRI segmentation is normally utilized for the purpose of measuring and visualizing several brain structures, for analyzing brain diseases, treatment progress and for image-guided involvements and surgical planning in order to diagnose it quickly. Image processing application has paved the way for the development of region based segmentation scheme in order to improve classification accuracy and to reduce the degree of complexity during the process of tumour analysis. In this research, used the most popular region based Active Contour Method (ACM) for effective brain MRI segmentation.

Image surface extraction: In general, Euclidean distance measurement is applied in standard FCM for the purpose of deformation of surfaces of the images. This measure had better results in noise-free image data, however usually fails miserably in case of noisy data. On the other hand, Kernel schemes (Xiao and Bargiela, 2010; Sikka *et al*., 2009) used in low noise free image data and extract the surfaces from brain MRI image data to recognize automatically the total surface of the outer and inner boundaries of cerebral cortical gray matter from human MR brain images and precisely locating the size of the tumor.

The original image was partitioned using KFCM and the controlled action of the edge indicator function was increased. The outcome of KFCM segmentation was employed to obtain the initial contour of level set method. With the assistance of the new edge indicator function, results of image segmentation demonstrated that the improved algorithm can accurately extract the related Region of Interest (RoI). With the same computing proposal, the average time cost was lesser. On the other hand, the KFCM is extremely responsive to noise, some redundant boundaries were appeared in the candidates. Then to overcome this problem, the method of edge detection is formulated. Kernel Fuzzy C-Means (KFCM) was employed to produce an initial contour curve which overcomes leaking at the boundary at some point in the curve propagation. Initially, KFCM algorithm calculates the fuzzy membership values for every pixel. In accordance with KFCM, the edge indicator function was redefined. Define a nonlinear map as:

$$\Phi I = \Phi(i) \in S \tag{1}$$

Where indicates the image data space and is the transformed feature space with higher even unlimited dimensions. The KFCM (Wu *et al*., 2003) diminishes the following objective function:

$$IM_e(X, Y) = \sum_{a-1}^{cl} \sum_{a-1}^{n} f^{e}_{a,b} \left\| \phi\left(i_a - \phi\left(f_a\right)\right) \right\|^2 \tag{2}$$

Where the transformed feature space indicates the number of cluster centers and stands for the number of datapoints. The $f_{a,b}^{e}$ decides the fuzzy membership of pixels and defines the fuzzification exponent. The kernel function is given as:

$$Ker(i,j) = \exp\left(-\frac{\|i-j\|^2}{2\alpha^2}\right) \quad (3)$$

Kernel induced new metric in the data space is given as:

$$d(i,j)\Delta\|\phi(i)-\phi(j)\| = \sqrt{2(1-Ker(i,j))} \quad (4)$$

The fundamental concept of KFCM (Wu *et al*., 2003) is to initially map the input data into a feature space with higher dimension by means of a nonlinear transform and subsequently carry out FCM in that feature space. As a result, the original complex and nonlinearly separable data structure in input space possibly will become simple and linearly separable in the feature space following the nonlinear transform. Hence, it is easy to get better performance in the following segmentation process with this generated initial contour.

Segmentation of brain MRI using region based Active Contour Model (ACM): Segmentation by means of ACM (Snakes) was introduced by Kass *et al.* (1988). The fundamental concept of the active contours or deformable models, for image segmentation is relatively uncomplicated. The user indicates an initial guess for the contour which is subsequently moved by image driven forces to the boundaries of the preferred objects.

Most commonly applied scheme of medical image segmentation is level set scheme or ACM. This entrenched scheme of segmentation is applied in order to obtain promising results of segmentation with accuracy and provide closed and smooth contour of object boundary which assist in extracting the features like texture and shape of the image data. This scheme of segmentation is categorized into two broad classes. First class is edge-based scheme of segmentation uses gradient to show contour evolution. Because of the use of gradient, segmentation is susceptible to noise and weak edges. At the same time, second class is region based scheme make use of the region descriptor like intensity, texture, shape etc., to identify RoI, to show curve evolution (Wang *et al*., 2009). Region based scheme segmentation provide enhance results even in the occurrence of noise and edge leakage of object boundary since this is less susceptible to initial contour location. Here, majorly concentrated on region-based ACM with level set formulation for image segmentation.

Active contour models: ACM are categorized into two, namely: edge-based and region based models. The edge-based model makes use of the gradient of the image to terminate the contour during evolution for the purpose of boundary detection of the foreground object. A region-based ACM makes use of statistical details of regions both inside and outside the curve for contour evolution, for instance, the Chan-Vese (C-V) model (Wang *et al*., 2010).

A region-based active contour model: This model based on the assumption that the pixel regions of the image are statistically homogenous. It works extremely well even with noisy, blur images and images that have multiple holes, disconnected areas, etc. In MRI brain image analysis, the region based ACM since takes global properties of images like contour lengths and MRI image pixel regions as alongside local properties like gradients. The energy minimizing function can be given as follows:

$$\text{In}\,P(I_3|p) = \iint_A^0 I_3(x,y)\,dA \quad (5)$$

Where is the intensity at the pixel location in the image and the integral gives the total area enclosed by the curve. As is evident, the region-based information visually improved the segmentation quality compared to the one using only gradient information.

Feature extraction method for brain MRI image analysis: After segmentation, the following features are extracted from the brain MRI images such as texture and shape. The feature of these images can be stored for further analysis. Feature Extraction is a one of the important process in MRI medical image based tumour analysis. The feature extraction process is used for creating a representation or transformation from the original image. In the MRI medical images have the primitive features like texture, shape, edge, darkness, etc. From these features, the most promising features like texture and shape/edge are extracted for classification accuracy in the proposed methodology. The variation of each pixel with respect to its neighboring pixels of the images defined as a texture. Hence, these textural details of MRI image regions can be compared with a texture template and extracted using Hybrid Wavelet Transformation Method. The shape/edge is simply a large and frequently changed. The shape features of the MRI images are extracted using Sobel and Canny Edge Detection Method. Both of these two types of feature descriptors are mainly used most often during feature extraction process in MRI brain image based tumour analysis process.

Feature extraction is a one of the important process in MRI medical image based tumour analysis. The feature extraction process is used for creating a representation, or transformation from the original image. In the MRI medical images have the primitive features like texture, shape, edge, darkness, etc. From these features, the most promising features like texture and shape/edge are extracted for classification accuracy in the proposed methodology. The variation of each pixel with respect to its neighboring pixels of the images defined as a texture. Hence, these textural details of MRI image regions can be compared with a texture template and extracted using Hybrid Wavelet Transformation Method. The shape/edge is simply a large and frequently changed. The shape features of the MRI images are extracted using Sobel and Canny edge detection method. These two types of feature descriptors are mainly used most often during feature extraction process in MRI brain image based tumour analysis process. The texture and shape feature extraction technique are described in detail as follows.

Texture feature extraction (hybrid wavelet transform): In brain MRI image analysis, an initial assumption of characterizing image texture is that all the texture information is contained in the gray-level value matrices of MRI image. Hence, all these textural features are extracted from these gray-level value matrices. The energy measures is mostly relate to specific textural characteristics of the MRI image. Other measures characterize the complexity and nature of gray level transition which occur in the MRI image. Even though, these features contain information about the textural characteristics of the image, it is hard to identify which specific textural characteristic is represented by each of these features.

Texture feature extraction is a most important stage in MRI image analysis in which texture features of each image is separately extracted from MRI by wavelets which considers better method to extract most emphasizing pixels present in images to improve results. To decompose data into different frequency components wavelets mathematical functions are used and then each element is studied having resolution matched to its degree. For analysis of complex datasets wavelet is a new powerful mathematical tool. Fourier transform fails due to the redundant set of features and only give frequency information that is not spatially localized but wavelet provides time frequency information which is localized in space and perfect tool for pattern recognition tasks

Hybrid discrete wavelet-cosine modulated wavelet transform: The proposed system uses the Discrete Wavelet Transform (DWT) coefficients as feature vector. The wavelet is a powerful mathematical tool for feature extraction and has been used to extract the wavelet coefficient from MR images. Wavelets are localized basis functions, which are scaled and shifted versions of some fixed mother wavelets. The main advantage of wavelets is that they provide localized frequency information about a function of a signal which is particularly beneficial for classification. A review of basic fundamental of wavelet decomposition is introduced as follows: The continuous wavelet transform of an image single s(t), square-integrable function, relative to a real-valued wavelet, (t) is defined as:

$$\mathrm{DWT}\varphi(x,y)\int_{-\infty}^{\infty} f(u)\times\varphi u,v(t)\,dt \tag{6}$$

Where: $\varphi_{u,v}(t)=\dfrac{1}{|\sqrt{u}|}$

and the wavelet $\varphi_{u,v}$ is computed from the mother wavelet by translation and dilation, wavelet, a the dilation factor and b the translation parameter (both being real positive numbers). Under some mild assumptions, the mother wavelet satisfies the constraint of having zero mean. Equation 6 can be discretized by restraining to a discrete lattice to give the Discrete Wavelet Transform (DWT). The Discrete Wavelet Transform (DWT) is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale. DWT can be expressed as:

$$\mathrm{DWTy}(n)=\begin{cases} d_{i,j}=\sum\left(y(n)h\times i(n-2ij)\right) \\ d_{i,j}=\sum\left(y(n)g\times i(n-2ij)\right)\end{cases} \tag{7}$$

The detail components in signal y(n) and correspond to the wavelet function, where as refer to the approximation components in the image signal. The h(n) and g(n) in functions the equation represent the coefficients of the high-pass and low-pass filters respectively, whilst parameters refer to wavelet scale and translation factors. The main feature of DWT is multiscale representation of function. By using the wavelets, given function can be analyzed at various levels of resolution. In texture feature extraction using DWT, the segmented original image is process along the x and y direction by h (n) and g (n) filters which is the row representation of the original image. As a result of this transform there are 4 sub band (LL, LH, HH, HL) images at each scale. The sub bands of the images are used for cosine modulated WT calculation at the next level. Thus, the different sub bands are generated using DWT.

After that the cosine-modulated wavelet transform (Qiao *et al*., 2006) is applying a number of sub-bands which are generated using DWT in MRI image. The magnitudes of wavelet coefficients In particular sub-bands are greater for images with a strong textural content at the frequency and orientation represented by that sub-band. Therefore, the textural features of MRI image can be represented by a feature vector that contains the average coefficient magnitude, known as averaged energy function.

The energy distribution has important discriminatory properties for images and as such can be used as a feature for MRI image classification. This work used energy signature for extraction of texture features as it reflects the distribution of energy along the frequency axis over scale and orientation. The discriminatory properties of the energy distribution in sub-bands result in texture features that have been observed to yield good characterization of textures for MRI image classification. The energy feature of the image is given by:

$$E_I = \frac{1}{MxN}\sum_{i=1}^{M} = 1\left|x(i,j)\right|, for s = 1,2..Q \tag{8}$$

Where, x is wavelet decomposed image for any sub-band of dimension M×N. For-level decomposition of the image, the size of the feature vector is Q = (3×K+1). since different features have different range of possible values and the entire feature may not have the same the same level of significance because after decomposition of image, the sub-bands with higher resolution corresponds to noise and may not valuable for classification. So, all these feature values are normalized in the range of 0 and 1 by the maximum value in the feature space before classification of these MRI image.

Shape feature extraction: For shape feature extraction in brain MRI image analysis, edge detection is a most important process. Shape feature extraction in image analysis requires the extracted edges to be connected in order to reflect the boundaries of objects present in the image. Then this shape feature extraction based on the edges in MRI brain image process is very useful further computational process. The various gradient operators used for edge extraction, here this proposed Shape Feature Extraction Method used for Sobel and Canny Method.

Edge detection Methods; Sobel and Canny: One of the most popular features for image classification is edges. Edges refer to boundaries of an object surface where the intensities change sharply. This proposed edge detection method used Sobel and Canny along with the gradient operators to extract the shape features in form of connected boundaries. The Sobel operator is one of the most commonly used edge detectors. The magnitude of the gradient of the Sobel operator is computed by:

$$MN = \sqrt{Grad_x^2 + Grad_y^2} \tag{9}$$

where the partial derivatives are computed by:

$$Grade_X = \left(a_2 + ca_3 + a_4\right) - \left(a_0 + ca_7 + a_6\right) \tag{10}$$

$$Grade_Y = \left(a_0 + ca_1 + a_2\right) - \left(a_6 + ca_5 + a_4\right) \tag{11}$$

with the constant the other gradient operators, $Grad_x$ and $Grad_y$ can be implemented using following convolution masks:

$$Grad_x = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}, Grad_y = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \tag{12}$$

That this operator places an emphasis on image pixels that are closer to the center of the mask.

Canny edge detector uses a filter based on the first derivative of a Gaussian because it is susceptible to noise present on raw unprocessed image data, so to begin with the raw image is convolved with a Gaussian filter. Canny operator is nothing but gradient of Gaussian filtered image. The convolution masks of canny operators are given as:

$$Grad_x = \begin{bmatrix} -2 & -2 \\ 2 & 2 \end{bmatrix}, Grad_y = \begin{bmatrix} 2 & 2 \\ -2 & -2 \end{bmatrix} \tag{13}$$

The edge detection using canny operator choose thresholds to get the edges of the images, the chosen higher threshold always is three times of lower threshold. Handle the MRI image pixels between the lower threshold area and higher threshold area. This will give a thin line in the output MRI image which is more efficient for final classification process in brain MRI analysis.

These feature extraction process resulting texture and shape feature spaces are selected by using PCA and the selected significant features are further optimizing, the meta-heuristic optimization Firefly algorithm, then these optimized features are fed into the ANN with MLM algorithm for detection of tumors from brain MRI and classified MRI as tumourous and non-tumourous. The performance of the feature selection and hybrid classifier in classification process is described as follows.

Feature selection using PCA: The proposed research also notes that there are always multiple feature values from both textural and shape feature extraction, so this research propose to take the significant feature of one feature component. As a result, this proposed research devises the following algorithm B to perform feature selection:

Step 1: Calculate the covariance matrix of PCA using the original training samples, then solve all the feature vectors and values.

Step 2: Select the feature vectors corresponding to the first m largest feature values and denote these vectors by $(V_1, \ldots v_m)$, respectively.

Step 3: Calculate the contribution to the feature extraction result, of the feature component as follows:

$$c_j = \sum^m{}_p = |1 v_{pj}|$$

Where:

v_{pj} = The jth entry of v_p, 1, 2,....N, p 1, 2,....m

$|v_{pj}|$ = The absolute value of $|v_{pj}|$

Step 4: Then, this work sort c_j in the descending order and use to store the order, where j = 1, 2,....N. For example, if c_3 and c_t are respectively, the first and second largest among all the c_j, j = 1, 2,....N, then let d_1 = s and d_2 = t which means that the sth and tth feature components of the original samples are the two most important features. If n-dimensional features are required, then the feature selection result will be d_1th d_2th. The d ņ the feature components. Here, this research used to select the energy and gradient feature components for an efficient MRI image classification results.

Classification of brain MRI image using hybrid Classifier: Hybrid FAMLM is an edge based classifier which achieve better classification performance compared to other algorithms. In case of proposed brain MRI analysis, extracted image features from after segmentation process are used to further classification, and the proposed hybrid FAMLM classifier used to classified brain MRI images as normal and abnormal, compare to the existing approaches. The procedure of the classifier used in this proposed method explained in detail as follows.

Proposed Firefly algorithm with modified Levenberg-Marquardt for classification: Swarm Intelligence Firefly Algorithm (FA) is meta-heuristic algorithm which is based on the flashing behaviours of the firefly swarm. The main principle for the sparkle of fireflies is to signal to attract other fireflies. The assumption of FA consists of three rules. They are describes as follows:

- All fireflies are unisex thus that one firefly will be fascinated to other fireflies regardless of their sex
- (An essential and motivating behaviour of fireflies is to radiance brighter mainly to attract victim and to share food with others
- Attractiveness is comparative to their brightness, so each agent firstly travels toward a neighbour that glows brighter

In the FA, the fireflies are randomly spread in the search space of the feature vectors from feature extraction process which was performed at early stage of this proposed brain MRI analysis. The fireflies grasp a luminescence excellence, called luciferin, which emanate light proportional to the quality. Every firefly is attracted by the brighter glow of other estimated fireflies. The attractiveness reduces as their distance increases. If there is no brighter one surrounded by the scope of a firefly, it will travel randomly in the search space. In this brain MRI image analysis application, the decision variables are the three spatial transform parameters as and The brightness is associated as the objective function is formulated as equation.

The variation of the light intensity of the fireflies: The brightness is correlated to the feature vector values, hence for a maximization/minimization problem; a firefly with advanced intensity will attract another firefly with higher probability and vice versa. Suppose that there survives a swarm of n fireflies and x_j stands for a solution for a firefly i, whereas f(xi) signifies its corresponding fitness value of the feature vectors. Here, the brightness B of a firefly is correspondent to the fitness value Bi = f(xi) $1 \leq I \leq n$.

Optimization based on the attractiveness of the Swarms (fireflies) Movements: The attractiveness of the firefly is proportional to the light intensity obtained by the adjacent fireflies. Assume ζ_0 is the attractiveness with distance = 0, hence for two fireflies I and j at locations $x_i$and x_j their attractiveness is calculated as:

$$\xi d(i,j) = \xi_0 0 \exp\{-\gamma d(i,j)^2 \quad (14)$$

$$d(i, j) = \|x_j - x_j\| \tag{15}$$

Where:

d (i, j) = The distance between fireflies
I, j, γ = The light amalgamation coefficient

Understand firefly j is brighter than firefly i, then firefly i will move to a new position as:

$$xi(t+1) = x_i t + \xi \exp\{-\gamma d^2\}(x_j - x_i) \tag{16}$$

Thus, the extracted features are optimized using FA algorithm and then these feature vector values are trained using the Levenberg-Marquardt algorithm with artificial neural network. The detail description of the MLM with ANN described in detail as follows.

Modified Levenberg-Marquardt with Artificial Neural Network: The neural network are non-linear statistical data modeling tools and can be used to model complex relationships between inputs and outputs or to find normal and abnormal classes in a MRI image dataset. Artificial neural network is a popular type of network that is very useful for MRI image classification. This training network is used with Modified LM for tumour diagnosis process in MRI image analysis. The Modified Levenberg-Marquardt algorithm (MLM) (Hagan and Menhaj, 1994) is a classification algorithm which is used in Artificial Neural Networks (ANN) for training. MLM classifier is popular in the ANN domain.

Modified LM algorithm: Considering Levenberg-Marquardt uses approximated Hessian matrix in the following Newton-like update:

$$X_k + 1 = X_k - \left[J_k(a)^T J_k(a) + \tau I\right]^{-1} J_k(a) T_{ek} \tag{17}$$

Where:

x_{k+1} and x_k = The points of Newton method at kth iterartion
τ = The learning rate of network
J = The Jacobian matrix
α = The vector
e_k = The error vector

When the scalar value is zero, this is a Newton's Method, using the approximate Hessian matrix. When τ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum so, the aim is to shift toward Newton's method as quickly as possible.

Thus, this function is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

There is used gradient can be computed as, gk = $J(a)^T e$ and the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training neural networks), then the Hessian matrix can be approximated as:

$$H = J(a)^T J(a) \tag{18}$$

In Newton's Method, Hessian approximation process step is not well conditioned. The vector error analysis definitely establishing that the Cholesky Stable algorithm, that assumes the Hessian matrix is sufficiently positive definite in LM. The main drawback of the previous research is when the value of n is large, here n is a parameter of vector, it is expensive both in computational effort and memory to compute the error reduction process. When is sufficiently positive definite, it is also unnecessary. Since, Cholesky is so cheap, it is always worth. In order to overcome aforementioned problem, the Hessian matrix is modified to compute a search direction based on modifying the Cholesky factorization.

Let $\bar{R}$ denote the Cholesky factor generated by this algorithm, then a is chosen such that $|\bar{R}\_(i,j)| \le \alpha$ where $a^2 = \max\{\gamma, \xi / n, \delta\}$ γ and ξ are the largest in modulus of the diagonal and off-diagonal elements of respectively and as beforeis some small positive scalar.

It can be shown that $\bar{H} = H + E$ E is a diagonal matrix, $\|E\|$ is bounded and $\bar{H}$ has a bounded condition number. The algorithm requires almost the same computational effort as the Cholesky algorithm.

Let $\bar{R}_k$ denote the Cholesky factor of $\bar{H}_k$. It follows a suitable sequence of sufficient descent search directions in network, $\{pk\}$ are obtained by solving $(\bar{R}_k^T \bar{R}_k) pk = -gk$. When H° is sufficiently positive definite then in the neighborhood of the solution $H_k = \bar{H}_k$ and Newton steps are taken, a modified direction as defined avoids saddle points.

For the Newton Method this approximation can be employed for this modified Hessian and subsequently to solve:

$$J(a)^T J(a_k) p_k = -J(ak)^T F(a_k) \tag{19}$$

Where is the vector-valued function, then to calculate the search direction pk and then let $a_k+1 = a_k+p_k$. More willingly than approximating the Hessian as in Eq. 20, the outline term in Eq. 19 can be given as by τI where $\tau \geq 0$. Following this, the Hessian is approximated as:

$$H \approx J(a_k)^T J(a_k) + \tau I \tag{20}$$

Where:

J = The Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases

e = The vector of network errors

The Jacobian matrix can be computed through a standard back propagation technique that is much less complex than computing the Hessian matrix. Now to find descent search direction, Eq. 12 is solved:

$$\left[J(a)^T J(a) + \tau I\right] p = -J(a)^T F(a) \tag{21}$$

After that, the performance index of the back propagation neural network defined by:

$$F(w) = gi(a) gi(a)^T \tag{22}$$

Where $w = [w1, w2, ..., w_n]$ consists of all weights of the network, gi (a) is the gradient error vector comprising the error for all the training examples. When training with the LM method, the updating of weights Δw can be obtained as:

$$\Delta w = -\left[\tau I + \sum J(a)^T J(a)\right]^{-1} \tag{23}$$

Where:

J = The Jacobian matrix

I = The identity matrix

τ = The learning rate which is to be updated using the depending on the outcome

Based on LM classification algorithm, updates the ANN weights as:

$$\Delta w = -\left[\tau I + \sum J(a)^T J(a)\right]^{-1} \tag{24}$$

Where:

J = The Jacobian matrix of the error gradient g_i (α) evaluated in vector

I = The identity matrix

$g_i(\alpha)$ = The error of the network

The parameter is increased or decreased at each step. If the error gradient is reduced, then τ is divided by a factor α and it is multiplied by α in other case while updating the network weights.

It calculates the network output, the error vectors and the Jacobian matrix for each pattern. Then, it computes Δw using Eq. 24 and recalculates the error with $w+\Delta w$ as network weights. If the error has decreased, τ is divided by α, the new weights are maintained and the process starts again; otherwise τ is multiplied by α, Δw is calculated with a new value and it classifies again. The process is repeated until the error decreases. When this happens, the current iteration ends.

Hybrid algorithms: Here, the hybridization refers to the inclusion of problem-dependent knowledge in a general search template (Cotta and Troya, 1998). The hybrid algorithms that used in this classification work are combinations of two algorithms, where one of them acts as an operator in the other. Here, this proposed work combines a FA with the Modified LM (FAMLM). In this case, the problem-specific algorithm (MLM) is used as a mutation-like operation of the general search template (FA). The Hybrid Classification algorithm using here in shown as algorithm B.

Algorithm B; Algorithm for Hybrid FA-MLM:

Begin
1) Objective function: (fx, $x = x_1, x_2..., xd$)
2) Generate an initial population of fireflies x_i(i-1, 2...n)
3) Formulate light intensity B so that it is associated with f(x)
(for example,for maximization problems, $B \propto fx$ or simply $B = f(x)$:
4) Define absorption coefficient γ
While (t <Max Generation) for I = 1: n(all n firefiles)
for j = 1: n(n firefiles)
move firefly i towards j:
end if Vary attractiveness with distance r via exp $(-\gamma d)$:
Evaluate new solutions and update light intensity;
end for j end for i Rank fireflies and find the current best;
end while
Post-processing the results and classification;
Initialize ANN Weights;
while not Stop Criterion do
Calculates for gradient error $g_i(\alpha)$ each i jth element;
J_1: = $\Sigma J(w+\Delta w)^T gi(\alpha)$ $(w+\Delta w)'$;
Calculates $J(\alpha)$ for each elements;
repeat
Calculates Δw;
J_2: = $\Sigma gi(\alpha)$;
if ($J_1 <= J_2$) then
$\tau = \tau * \alpha$;
endif;
until ($J_2 < J_1$);
$\tau = \tau / \alpha$;
End while;
End

The outcome of FAMLM classifier decides whether a sample image dataset is tumorous or non-tumorous.

RESULTS AND DISCUSSION

In the proposed system, brain tumor diagnosis from brain MRI images, for tumor diagnosis brain MRI images were classified by using different optimization algorithm and classification algorithm. The results obtained for the classification algorithms are given in this study.

Performance analysis: Here, this proposed classification algorithm's sensitivity, specificity and classification accuracy rate calculated and compared with the different classification methods with the support of number of input brain MRI DiCom Image dataset.

Sensitivity: Sensitivity (or) recall rate is the probability of the actual positive (tumour or non-tumour) classes which are identified correctly:

$$\text{Sensitivity} = TP / \left(\left(TP + FN\right)\right) \times 100 \quad (25)$$

Figure 2 represents the sensitivity comparison among the three different algorithms with proposed classification algorithm.

In Fig. 2, the graph shows that the sensitivity rate comparison of existing and proposed classification algorithm results based on two parameters such as sensitivity and number of given no. of MRI Input images.

Specificity: Specificity (or) true negative rate is the probability of actual negative classes (tumour or non-tumour) which are identified correctly:

$$\text{Specificity} = \frac{TN}{\left(TN + FP\right)} \times 100 \quad (26)$$

Where:

TP (True Positive) = The number of correctly classified tumor cases

FP (False Positive) = The number of incorrectly classified tumor cases

FN (False Negative) = The number of incorrectly classified Non-tumourous

TN (True Negative) = The number of correctly classified Non-tumourous

Figure 3 clearly describes the proposed algorithm has a high specificity rate compare to the previous classification algorithm. The graph shows specificity rate comparison of both the proposed and existing methods.

Classification accuracy: The problems of segmentation and classification are intersecting each other because segmentation implies a classification while a classifier implicitly segments an image. The segmentation results are further used in classification process.

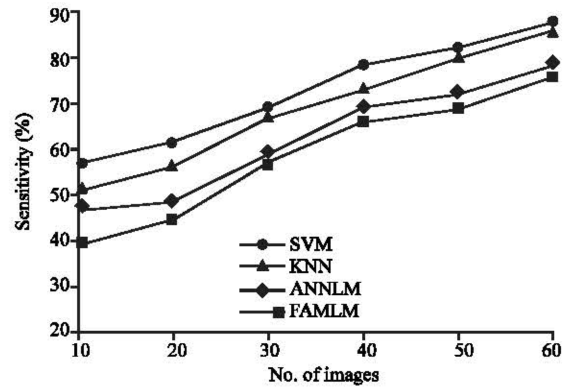

Fig. 2: The sensitivity rate of the proposed and existing algorithm

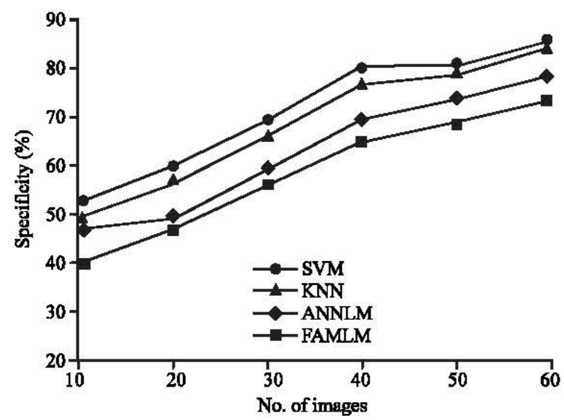

Fig. 3: The specificity rate of the proposed and existing algorithm

Classification accuracy defined as the percentage of correct classification of tumour and non-tumour classes from the MRI brain image. The accuracy rate is denoted as follows:

$$\text{Accuracy} = \frac{TP + TN}{\left(TP + FN + FP + TN\right)} \times 100 \quad (27)$$

Figure 4 shows the influence of the segmentation process results in the proposed and existing classification algorithms in the Brain MRI image analysis. The proposed region based ACM segmentation increases the proposed classification algorithm accuracy rate. The graph will shown the influence of the segmentation in the proposed and existing classification algorithm.

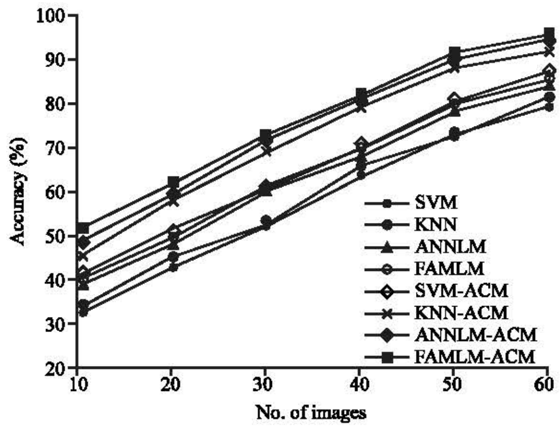

Fig. 4: The overall comparative classification accuracy of the proposed and existing algorithm

CONCLUSION

In this proposed method shown that a hybrid MLM classifier with firefly algorithm to differentiate normal and abnormal brain MRI images. The proposed technique consists of four stages, mainly, preprocessing, segmentation, feature extraction using ACM with surface feature extraction KFCM method and classification using swarm intelligent based Firefly with neural network based MLM classifier correspondingly. In the preprocessing stage, an Adaptive Median Filter (AMF) is used to remove the noise and thus preserving the edge point of the given input MRI images. In the segmentation stages, the extracted surface features are using segmenting based on ACM into important regions. After segmentation process features are extracted using hybrid wavelet transform and shape features are extracted using Sobel and canny, at last stage to classify normal and abnormal brain MRI images hybrid classifier is used. According to experimental results, the proposed hybrid classifier method is efficient for classification of human brain MRI into malignant and benign classes. The future work will focus on include additional feature information for most accurate classification results in brain MRI analysis.

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