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Tumor Diagnosis in MRI Brain Image using ACM Segmentation and ANN-LM Classification Techniques

A. Shenbagarajan[1]*, V. Ramalingam[1], C. Balasubramanian[2] and S. Palanivel[1]

[1]Department of Computer Science and Engineering, Annamalai University, Chidambaram - 608002, Tamil Nadu, India; asrme2008@gmail.com, aucsevr@gmail.com, spal_yughu@yahoo.com
[2]Department of Computer Science and Engineering, P. S. R. Rengasamy College of Engineering for Women, Sivakasi - 626140, Tamil Nadu, India; rc.balasubramanian@gmail.com

Abstract

Background: Magnetic Resonance Images (MRI) is an important medical diagnosis tool for the detection of tumours in brain as it provides the detailed information associated to the anatomical structures of the brain. MRI images help the radiologist to find the presence of abnormal cell growths or tumours. MRI image analysis plays a vital role in diagnosis of brain tumours in the earlier stages and treatment of diseases. **Methods:** Therefore, this paper introduces an efficient MRI brain image analysis method, where, the MRI brain images are classified into normal, non cancerous (benign) brain tumour and cancerous (malignant) brain tumour. This proposed method follows four steps, 1. Pre-processing, 2. Segmentation, 3. Textural and shape feature extraction and 4. Classification. In this proposed MRI image analysis using the region based Active Contour Method (ACM) used for segmentation and Artificial Neural Network (ANN) based Levenberg-Marquardt (LM) algorithm used for classification process, which used to efficiently classify the MRI image as normal and Tumourous. **Findings:** The results revealed that the proposed MRI brain image tumour diagnosis process is accurate, fast and robust. The classifier based MRI brain image processing approach produced the best MRI brain image classification with use of feature extraction and segmentation results, in terms of accuracy. Best overall classification accuracy results were obtained using the given DioCom Images; The performance results proven that there is not sufficient result given to the classification process when it perform separately. With the use of ACM segmentation and feature extraction approaches, the proposed LM classification approach provides better classification accuracy than the existing approach. **Application:** The proposed MRI image based brain tumour analysis would efficiently deal with segmentation and classification process for brain tumour analysis with use of feature extraction methods, so this method can yield the better result of brain tumour diagnosis in advance where this method using in medical fields.

Keywords: Active Contour Method (ACM), Artificial Neural Network (ANN) based Levenberg-Marquardt (LM) Algorithm, Magnetic Resonance Images (MRI)

1. Introduction

Magnetic Resonance Imaging (MRI) is a kind of medical image processing approach[1]. It is mainly used by the radiologist for the purpose of visualization of the inner composition of the human body. It gives valuable details regarding human soft tissues anatomy. It effectively assists in the process of diagnosis of the brain tumour. Images captured with MRI are employed for analyzing and investigating the behaviour of the brain. MRI of the brain is often used to monitor tumour response to treatment process.

The segmentation and classification of the brain tumour from the MRI is extremely vital in the field of medical diagnosis, since it gives details related with the anatomical compositions in addition to the potential

**Author for correspondence*

abnormal tissues essential for carrying out treatment and patient follow-up. It can also be supportive in case of general modelling of pathological brains and the building of pathological brain atlases[1]. A fine example is to analyze and approximate quantitatively the development process of brain tumours, and to evaluate the reaction to diagnosis and in guiding suitable therapy in serial studies[2–4]. Despite several attempts and potential results in the medical imaging community, correct and reproducible segmentation and characterization of abnormalities are continue to be a most tricky and complicated task owing to the diversity of the possible shapes, positions and image intensities of several categories of tumours. This MRI brain image involves a variety of regulations together with medicine, MRI physic, radiologist's view and image investigation in accordance with the intensity and shape.

MRI brain image analysis, Brain tumour segmentation process[5–6] consists of separating the different tumour tissues, such as solid tumour, edema and necrosis from the regular brain tissues, for instance, Gray Matter (GM), White Matter (WM) and Cerebro-Spinal Fluid (CSF). MRI image segmentation is a progression of dividing an image into several homogeneous areas, in order that significant information regarding the image can be acquired and several analysis can be done on that segmented image. Extraction of brain tumour region needs the segmentation of brain MRI into two segments. First segment includes the regular brain cells and the other segment includes the tumorous cells of the brain. This process is binary in nature. Classification[7] is the technique for classifying the images into equivalent classes. When the brain images are obtained, they are classified into normal and abnormal. In order to carry out the classification of the images effectively, different features[11] are extracted. This paper presents an overview of the simple and most relevant brain tumour analysis method which is applied after the acquisition of the MRI image from Database. Based on the advantages of MRI over other diagnostic imaging techniques, this work is focused on MRI brain tumour image analysis process, which consists of the following stages, 1. Pre-processing, 2. Segmentation, 3. Feature Extraction[8,9] and then finally 4. Classification[10]. In this MRI image analysis, initially the pre-processing stage is used for removal of unwanted noises from the MRI image, for that Bi-lateral filtering method is used and then that noise removed image is segmented using the ACM segmentation technique. The segmentation process is based on the region of the MRI brain images. From this segmented image, texture features are extracted using wavelet transformation method and shape features are extracted using sobel and canny methods[11,12] and then the MRI images are classified as normal or Tumourous using ANN-LM classification technique.

Wang et al.[13] formulated an automatic segmentation system for the purpose of MRI brain tumour. Local region-based active contour schemes were extremely appropriate in case of heterogeneous characteristics of brain MRI. However, the scheme is extremely responsive to preliminary contour, which normally needs physical setting. An automatic MRI brain tumour segmentation system were developed in accordance with the localized contour models, which can recognize tumour-dominant slice, fix primary contour automatically and segment tumour's contours from the entire MRI slices autonomously. K-means clustering and gray scale analyses were combined to identify tumour-dominant slice. Multi-threshold scheme with the support of erosion and dilation operators was implemented in order to get hold of an initial contour for the tumour-dominant slice. On the other hand, the segmentation contour from the local active contour models was implemented as initial contours of two-side neighbouring slices.

Andronesi et al.[14] formulated a new scheme that integrates a Two-Dimensional (2D), solid-state, HRMAS proton (1H) NMR scheme, TOBSY (Total through-Bond Spectroscopy), which considerably increases the benefits of HRMAS and a strong classification scheme. Here, they utilized just about 2 mg of tissue at 8 degrees C from each of 55 brain biopsies, and consistently detected 16 different biologically important molecular species. They employed the Minimum Redundancy/Maximum Relevance (MRMR) scheme as a strong feature-selection scheme together with the SVM classifier and recommended that molecular characterization of brain tumours based on extremely informative 2D MRS must allow to type and prognoses even untreatable patients with more accuracy in vivo.

Arizmendi, et al.[15] provided the improvement, execution and exploitation of computer-based Medical Decision Support Systems (MDSS) based on pattern recognition approaches holds the promise of considerably enhancing the feature of medical practice in diagnostic and prognostic processes. Here, the central part of a decision support system for brain tumour classification from Magnetic Resonance Spectroscopy (MRS) data is provided. It integrates the data pre-processing by means of Gaussian decomposition, dimensionality reduction by means of moving window with variance analysis and classification using Artificial Neural Networks (ANN). This scheme is found to provide better diagnostic classification accuracy in problems concerning diverse brain tumour pathologies.

Dubey et al.[16] formulated a scheme for the purpose of classification of the MRI of human brain by means of cosine modulated wavelet transform. Improved discrimination and low design execution complexity of the cosine-modulated wavelets has been successfully exploited to provide enhanced features and more precise classification outcome. This scheme includes two stages, to be exact, feature extraction and classification. During the first stage, the energy features are acquired from subband images got hold subsequent to decomposition by means of cosine modulated wavelet transform. During the classification stage, Bays classifier is utilized for the purpose of classifying the image as normal or abnormal.

Ghazali et al.[17] discussed the purpose of feature extraction scheme in image processing and to represent the image in its compact and distinctive form of single values or matrix vector. Low level feature extraction undergoes automatic extraction of features without doing any processing. Here, the author considered the utilization of high level feature extraction scheme to examine the quality of narrow and broad weed by means of implementing the 2 Dimensional Discrete Wavelet Transform (2D-DWT) as the processing scheme. Most transformation schemes generate coefficient values with the similar size as the original image. Additional processing of the coefficient values have to be applied to obtain the feature vectors. They also formulated an algorithm to execute feature extraction by means of the 2D-DWT and the obtained coefficients are employed to signify the image for classification of narrow and broad weed.

In case of all above-mentioned MRI image analysis methods, very promising classification and segmentation results have been reported for MRI image. In[13] presented an initial active contour model for segmentation and segmentation contour from the local active contour models was given as initial contours of two-side neighbouring slice of MRI image and this initial contour model provides the more efficient segmentation result in an automatic segmentation system. In[14] and[15] the neural network based LM used in Magnetic Resonance Spectroscopy (MRS) for the purpose of enhancing the quality of medical treatment in diagnostic and prognostic processes. In[16] described the cosine wavelet transform feature extraction method used for the better classification purpose and in[17] proposed the purpose of wavelet transform based feature extraction technique in MRI image processing and the obtained coefficients are employed to characterize the image for effective classification. From the inference of all the above mentioned methods, the problem of considering the current trend presented by newly consideration of an efficient classifier, which is combined with pre-processing, segmentation and texture and shape feature extraction process for accurate final classification results in the MRI image analysis, which is an important issue with tumour diagnosis attracted much attention in the recent years.

2. Proposed Methodology

In this proposed method of MRI brain tumour analysis consists of segmentation and classification system with feature extraction technique. Basic structure of this proposed methodology as shown in Figure 1, the proposed brain tumour analysis process mainly consists of four stages: Pre-processing using bilateral filtering method for removing noise from the MRI image, after removing of noise from the MRI image, segmentation is done using the region based active contour method, then texture and shape feature extraction from the MRI image, finally the feature extracted MRI image classified using network based LM algorithm and validation stages. The results of this proposed system clarified that this method can efficiently classified the MRI brain image into normal and Tumourous class. The proposed methodology is detail described here.

2.1 MRI Brain Image Dataset

A publicly available set of training data from The Digital Imaging and Communications in Medicine (DICOM) as an input data set[18] of the proposed methodology. DICOM consists of 80 images that contain brain tumours. It has no ground truth images for the contained images.

2.2 MRI Brain Image Pre-processing

In this MRI brain image analysis, pre-processing step is generally used to removing noise or denoising from the input MRI brain images. The goal of image denoising is to remove the noise from MRI image while retaining the

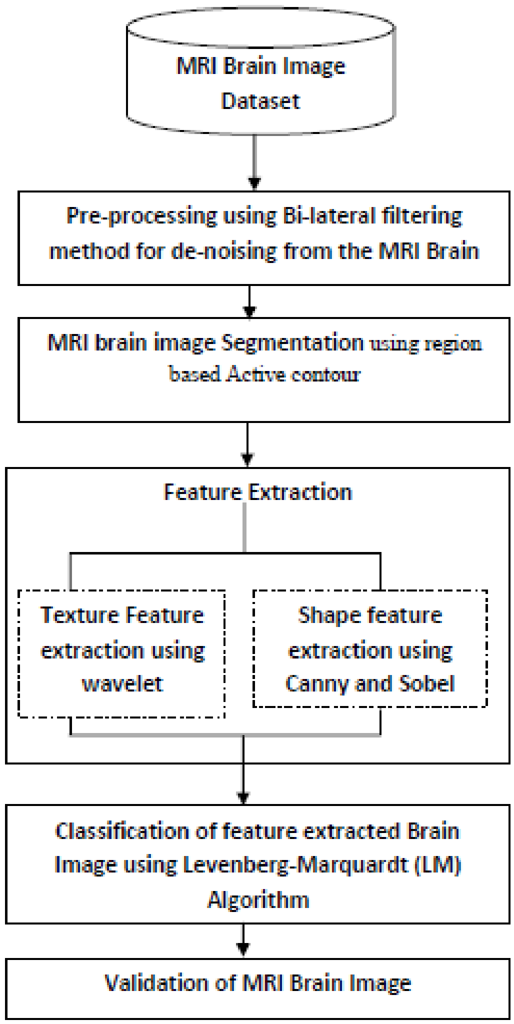

Figure 1. Process of proposed methodology.

important image features like edges, details as much as possible. Here this pre-processing method introduced the non-linear bilateral filtering method for removal of noises from the MRI image. Filtering is a part of image enhancement which is used to enhance certain details such as edges in the image that are relevant to the application. In addition to that, filtering can also be used to eliminate unwanted elements of noise. The bilateral filtering removes noise from the MRI brain images while preserving edges, by means of a nonlinear combination of nearby image values.

2.2.1 Bilateral Filtering for Removal of Noises from the MRI Images

The intensity value at each pixel in an MRI image is substituted with a weighted average of intensity values from close by pixels. This weight can be in accordance with the Gaussian distribution. Significantly, the weights based not only on Euclidean distance of pixels, however also on the radiometric distinctions (e.g., range dissimilarities, for instance, colour intensity, depth distance, etc.). This helps to preserve the sharp edges by systematically looping through every pixel and fine-tune weights to the neighbouring pixels of the MRI consequently. The bilateral filter is given as follows,

$$IM^{filtered} = \frac{1}{W_p} \sum_{x_i \in \Omega} IM(x_i) f_r(\|IM(x_i) - IM(x)\|) g_s(\|x_i - x\|) \quad (1)$$

Where the normalization term is given as,

$$W_p = f_r(\|IM(x_i) - IM(x)\| g_s(\|x_i - x\|) \quad (2)$$

Makes sure that the filter protects image energy and where $IM^{filtered}$ is filtered image, **IM** is the original input image to be filtered, x and x_i are the coordinates of the current image pixel to be filtered, Ω is the window centered in x, and f_r is the range kernel for the purpose of smoothing the dissimilarities in intensities. This function possibly be a Gaussian function, g_s is the spatial kernel for the purpose of smoothing dissimilarities in coordinates.

The weight W_p is allocated by means of the spatial proximity and the intensity dissimilarity[19]. For instance, consider an image pixel located at (i,j) which needs to be denoised in image using its neighbouring pixels and one of its neighbouring pixels is located at (k,l). Then, the weight assigned for pixel (k,l) to denoise the pixel (i, j) is given by:

$$w(i,j,k,l) = e^{\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2} - \frac{\|IM(i,j)-IM(k,l)\|^2}{2\sigma_r^2}\right)} \quad (3)$$

where σ_d and σ_r are smoothing parameters and **IM(i,j)** and **IM(k,l)** are the intensity of pixels **i.j** and **k,l** respectively. After calculating the weights, normalize them.

$$IM_D(i,j) = \frac{\sum_{k,l} IM(k,l) * w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)} \quad (4)$$

where I_d is the denoised intensity of pixel i, j. The output of this normalization step in pre-processing is the free noising MRI image and these images are used in the segmentation process in the MRI image analysis.

2.3 MRI Brain Image Segmentation

In MRI Brain Image analysis, segmentation is an important procedure, which is used to detect the tumours from the MRI brain image. In MRI image analysis, after pre-processing, the segmentation technique is used to detect a tumour inside an MRI brain image, the boundaries of structures in cases that these are ambiguous and the areas that radiopharmaceutical concentrate in a greater extent. Thus, the segmentation process serves in assisting the implementation of other procedures, in brain image analysis.

Many promising methods have been proposed for image segmentation, such as the region merging based methods[20], the graph based methods[21], and the Active Contour Model (ACM) based methods[22], etc. This proposed approach used region based ACM for segmentation, which aims to drive the curves to reach the boundaries of the input MRI brain images. The another edge-based ACM often utilizes the local image gradient information to build some stopping functions in order to drive the contour to stop at the object boundary, while the region-based ACM aims to drive the curve to evolve through region-based descriptors[23] which provide an efficient way for segmentation in MRI brain image analysis.

2.3.1 Active Contour Models

Active Contour models are classified into two, namely: Edge-based models and region based models[24]. The edge-based model utilizes the gradient of the image to stop the contour during evolution for boundary detection of the foreground object. A region-based active contour model uses statistical information of regions both inside and outside the curve for contour evolution, for example, the Chan-Vese (C-V) model[25].

2.3.1.1 A Region-based Active Contour Model for MRI Image Segmentation

This model is based on the assumption that the pixel regions of the image are statistically homogenous. It deals well with noisy images, blur images, and images that have multiple holes, disconnected regions etc. In MRI brain image analysis the region based active contour model since considers global properties of images such as contour lengths and MRI image pixel regions as against local properties such as gradients. The energy minimizing function can be represented as:

$$\ln P(I_s \,|\, p) = \int\int_A^0 I_s(x, y)dA \qquad (5)$$

Where $I_s\,(x, y)$ is the intensity at the pixel location (x, y) in the image, and the integral gives the total area **A** enclosed by the curve p. As is evident, the region-based information visually improved the segmentation quality compared to the one using only gradient information.

2.4 Feature Extraction

The transformation of segmented MRI image into its collection of features is regarded as feature extraction in MRI image analysis. Useful features of the segmented MRI image are extracted from the for the purpose of classification. It is a tricky process to extract an optimal feature-set for classification in MRI brain image. There are many techniques for feature extraction, in this proposed work used texture feature extraction based on wavelet transform[26] and shape feature extraction based on sobel and canny methods.

2.4.1 Texture Feature Extraction

Texture feature extraction is employed for the purpose of extracting texture features from the MRI brain image. After shape feature extraction, these two features independently are used for classification step in MRI brain image analysis.

2.4.1.1 Cosine-Modulated Wavelet Transform for Texture Feature Extraction

Through the process of applying the cosine-modulated wavelet transform[27], several sub-bands are produced in MRI. The extents of wavelet coefficients in a specific sub-band are larger for images with a strong textural content at the frequency and orientation indicated by that sub-band. As a result, the texture can be indicated as a feature vector that encloses the average coefficient extent, regarded as averaged energy function.

The energy distribution has significant discriminatory characteristics and this can be utilized as a specific feature during classification. This work makes use of energy signature for the purpose of extraction of texture features as it reproduces the distribution of energy along the frequency axis over scale and orientation. The discriminatory feature of the energy distribution in sub-bands end in texture characteristics that have been examined to provide better categorization of textures for MRI image classification. The energy feature E_I of the image is givenby,

$$E_I = \frac{1}{MxN}\sum_{i=1}^{M}\sum_{j=1}^{N}|x(i,j)|, \qquad (6)$$

Where x is wavelet decomposed image for all sub-band of dimension M×N. In case of K-level decomposition, the size of the feature vector is Q=(3*K+1). In view of the fact that different features have dissimilar range of feasible values and the complete feature might not have the equal level of impact, since following the decomposition of image, the sub-bands with large resolution corresponds to noise and might not helpful for classification. Accordingly, the entire feature values are normalized in the limit of 0 and 1 through the maximum value in the feature space prior to classification of these MRI images.

2.4.2 Shape Feature Extraction

After image segmentation, according to the a priori knowledge, shape feature extraction for the area of interest of image (i.e., edges) can be extracted. The shape representation of the MRI brain image can be considered as one of the important image discrimination factors, which can be used as feature vector for MRI Brain tumour analysis. Shape representation mainly can be represented as two types 1. Boundary based and 2. Region based. Generally gradient operators and morphological operations are used to extract the boundary of shape as edges present in the MRI brain image. To get the complete boundary of the shape in the MRI image in form of connected edges slope magnitude method is used with gradient operators.

In Edge detection for shape feature extraction in MRI brain image analysis, it can be used First Derivative Method (FDM). In FDM, First-order based edge detection-the first order derivative at a pixel is used to decide the presence of edges in the image. The first order derivative is searched for the maximum or the minimum value and the pixel containing this value is considered an edge. An example of this is the Sobel edge detector[28] Gradient corresponds to the first derivate, gradient operator is a derivative operator.

2.4.2.1 Sobel Method

Sobel method is applied to perform edge detection in MRI Brain image analysis. The Sobel edge detector use two masks with 3x3 sizes, one estimating the gradient in the x-direction and the other estimating the gradient in the y-direction[28]. The mask is slid over the MRI image, manipulating a square of pixels at a time. The algorithm calculates the gradient of the image intensity at each point, and then gives the direction to increase the image intensity at each point from light to dark. MRI image Edges areas represent strong intensity contrasts which are darker or brighter. Sobel algorithms work using a mathematical procedure called convolution and commonly analyze derivatives or second derivatives of the digital numbers over space.

Sobel is one of the most used operators. Sobel find edges of the MRI images in x-axis and in y –axis. It has two operators, for example one of them is to do horizontal direction detection, the other one is to do the Vertical direction detection, then put the results together. The Sobel edge detector calculates the gradient along the x and y direction separately. In Figure 2, Sobel edge detection templates are shown

$$Sx = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, Sy = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Figure 2. Sobel edge detection templates.

This work calculate horizontal and vertical gradient S_x, S_y, then it combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. This proposed work uses these numbers to compute the edge (gradient) magnitude and direction, which given by:

$$|S| = \sqrt{S_x^2 + S_y^2} \qquad (7)$$

$$\theta = \arctan(\frac{S_y}{S_x}) \qquad (8)$$

Edges of the images can now be extracted by a simple threshold.

2.4.2.2 Canny Edge Detection

Canny edge detection used function for canny operator. In the edge detection using canny operator initially, the canny operator used the Gaussian filter to do the image filtering, which is for smoothened the MRI image and then calculate the gradients and directions of each pixel using following edge detection templates and derivations. Template example is shown in the Figure 3.

$$U = \frac{1}{2}\begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix}, V = \frac{1}{2}\begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix},$$

Figure 3. Canny edge detection templates.

Then can get its gradient and direction, it is shown in the equation,

$$M(x.y) = \sqrt{U^2(x,y) + V^2(x,y)} \tag{9}$$

$$\theta = \arctan\left[\frac{V(x,y)}{U(x,y)}\right] \tag{10}$$

Where, x, y are the direction. Then do the Non-maxima suppression on the gradient of the image pixel and divide the two thresholds. The edge detection using canny operator choose the two 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.

These extracted texture and shape features can be further fed into the ANN with LM algorithm for Classification in MRI brain image analysis. The performance of the classifier in classification process, classifying the brain MR images into normal, benign and malignant brain tumours. The classification process is described as follows.

2.5 MRI Brain Image Classification

Neural Networks (NN) are extensively employed in the process of pattern classification, in view of the fact that they do not require any details regarding the probability distribution and the a priori probabilities of several classes. NN classification system imitates the human way of thinking and in certain scenarios, it provides the decision for more than one class to demonstrate the possibilities of some other infections. In case of brain MR image classification, as normal or abnormal, this method used a Back-propagation algorithm LM with Artificial Neural Network (ANNLM) to categorize inputs into the collection of target categories (normal or abnormal) in accordance with the feature extraction parameters.

The Levenberg-Marquardt (LM) scheme is a higher-order adaptive approach and considerably decreases the Mean Square Error of a neural network[30]. In this proposed work attempts to apply optimized LM scheme in order to diminish the errors during the process of classifying the tumour in brain images. LM is extensively used in the field of manufacturing and engineering optimization purpose, on the other hand, these scheme never been examined on a neural network for the use of medical condition classification. In this proposed work the MRI brain image is subjected to the ANN scheme by means of LM training in order to discover and categorize the occurrence of tumours in the MRI brain image and experiments are further done to decide the sensitivity, specificity and accuracy of the optimized LM scheme. The complete process used in tumours condition in MRI brain image classification is presented below.

LM Approach and Network architecture,

Consider a nonlinear model of the general form in MRI brain image classification,

$$x_i = p(y_i, \alpha) + \varepsilon_i \text{ where, (i = 1, 2, 3...m)} \tag{11}$$

Where α is a vector containing **n** parameters and m>n. Assume further that **g** is nonlinear in $\alpha^T = [\alpha_1, \alpha_2, \ldots\ldots \alpha_n]$. The approach of least squares is utilized for the purpose of estimating the indefinite parameters in case of a non-linear regression function. In proportion to this scheme, the estimates of $\alpha_1, \alpha_2, \ldots\ldots \alpha_n$ are obtained by minimizing the quantity,

$$\sum g_i^{\,2}(\alpha) \tag{12}$$

The sum of the squares of the errors of the predictions of the classification of the normal or abnormal brain images is derived by aforementioned, where:

$$g_i(\alpha) = x_i - p(y_i, \alpha) \tag{13}$$

As provided by nonlinear regression, the scheme of nonlinear least-squares data fitting has an exceptional form for the gradient and Hessian.

The classification problem is given as:

$$\min g(\alpha) = \frac{1}{2}\sum g_i(\alpha)^2 = \frac{1}{2}F(\alpha)^T F(\alpha) \tag{14}$$

Where **F** is the vector-valued function.

$$F(\alpha) = (g_1(\alpha), g_2(\alpha), \ldots\ldots, g_m(\alpha))^T \tag{15}$$

Note that the scaling by $\frac{1}{2}$ is to formulate the derivatives less jumbled. The constituents of $\nabla(\alpha)$ can be derived as follows:

$$\nabla g(\alpha) = J(\alpha)^T F(\alpha) \tag{16}$$

Where **J** is the Jacobian matrix with **ijth** element.

$$J_i, j = \frac{\delta p(y_{i,}\alpha)}{\delta \alpha_i} \tag{17}$$

i=1, 2, 3….,m and j=1,2,3..,n

$\nabla^2 g(\alpha)$ can be obtained through the process of differentiating in accordance with,

$$\alpha_j \nabla^2 g(\alpha) = J(\alpha)^T J(\alpha) + \sum g_i(\alpha) \nabla^2 g_i(\alpha) \quad (18)$$

Since it is anticipated that $g_i(\alpha)$ is in the order of zero, the summing up term can be disregarded. As a result, this proposed work can approximate $\nabla^2 g_i(\alpha)$ as

$$\nabla^2 g(\alpha) = J(\alpha)^T J(\alpha) \quad (19)$$

For the Gauss-Newton method this approximation can be employed for the Hessian and subsequently to solve,

$$J(\alpha)^T J(\alpha_k) p_k = -J(\alpha_k)^T F(\alpha_k) \quad (20)$$

to calculate p_k and then let $\alpha_k + 1 = \alpha_k + p_k$ More willingly than approximating the Hessian as in Equation (19), the outline term in Equation (18) can be given as by τI where τ ≥ 0. Following this the Hessian is approximated as

$$\nabla^2 g_i(\alpha) \approx J(\alpha_k)^T J(\alpha) + \tau I \quad (21)$$

Now to find search direction, **p**, the following equation is solved:

$$[J(\alpha)^T J(\alpha) + \tau I] p = -J(\alpha)^T F(\alpha) \quad (22)$$

After finding p, g (α+ p) has been assessed. When there has been an enhancement in the function value, subsequently consider α = α + p and τ = τ/2.

The termination condition is subsequently verified. When the termination condition is not satisfied, subsequently proceed with next iteration. On the other hand, the evaluation of g (α + p) does not provide an enhancement in the function value, and then consider τ = 2τ but α has not been transformed.

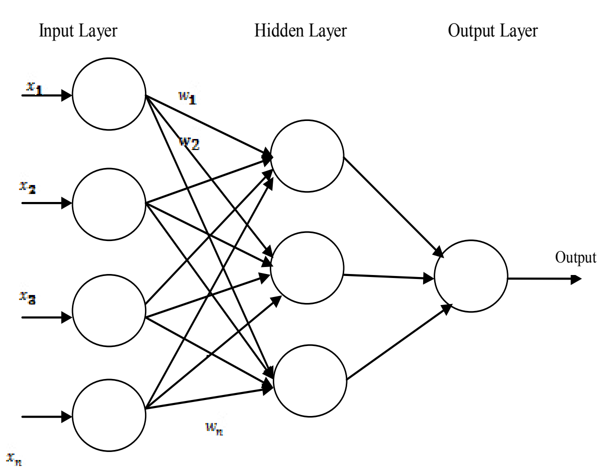

Figure 4. Basic structure of Artificial Neural Network.

The LM Algorithm steps as follows:

The LM is executed on constructed Artificial Neural Network. The Figure 4 shows that the basic architecture of the ANN.

LM Algorithm:

1. Compute the Jacobian Matrix with i,jth element
2. Compute the error gradient, $\nabla^2 g(\alpha)$
3. Approximate the Hessian using the cross product Jacobian, $\nabla^2 g_i(\alpha) \approx J(\alpha_k)^T J(\alpha) + \tau I$
Solve $[J(\alpha)^T J(\alpha) + \tau I] p = -J(\alpha)^T F(\alpha)$ o find p
Update the network weights **w** using p For improvement in the function value then let α = α+ p and τ = τ/2.
Recalculate the sum of squared errors using the updated weights
If the sum of squared errors has not decreased,
Discard the new weights, increase τ using α and go to step 4.
Else decrease τ using α and stop.

In this proposed work network structure, nodes are dynamically added until classification of the MRI brain image efficiency is accomplished. New node is placed dynamically during the learning rule update weights until it reaches the classification efficiency level in MRI image analysis. Consequently, the learning rule is still can be executed on network layer even if it is not completely well-organized and enables the network to produce classification efficiency. As the new node is added dynamically the search direction of LM is fixed to as steepest descent scheme when achieved efficiency is distant from classification efficiency. The Brain Tumour analysis with the LM algorithm is classified through input MRI brain image Dataset. The two classes are normal, which indicates the brain image have not tumours, and abnormal which indicates the MRI image have tumours. The main objective of this proposed classification has been to make use of the LM method in improving the classification accuracy of the neural network on the dataset applied for the MRI brain image analysis.

3. Experimental Results

Images acquired were in DICOM (Digital Imaging and Communications in Medicine)[18] format. The system was implemented using the functions available in MATLAB. In this proposed work, experiments have conducted on certain number of MR brain images of different patient. Firstly the images are divided into different blocks and features are extracted from each block. Then classification neural network based LM algorithm applied on each block of the image. A result of classification technique is as shown in Figures 4 to 6. Sensitivity, specificity, and accuracy are calculated for proposed method and compared to existing methods such as SVM, KNN[30]. These terms are used to describe the clinical efficiency of a final classification of MRI brain image.

3.1 Performance Evaluation

To evaluate the performance of the proposed classification approach, there are three performance parameters were considered: Sensitivity, specificity and accuracy. In this proposed DICOM MRI brain image data set consist of 80 images as testing data for the MRI image classification, in which 48 images representing as Tumourous, which are belongs to T1, T2 and PD weighted category and the same categorized 32 images are representing as non-Tumourous. The performance results were obtained using a MATLAB. The performance parameters are defined by the following formulae:

3.1.1 Sensitivity

Sensitivity (or) Recall (or) True Positive Rate is the probability of the actual positive classes which are identified correctly.

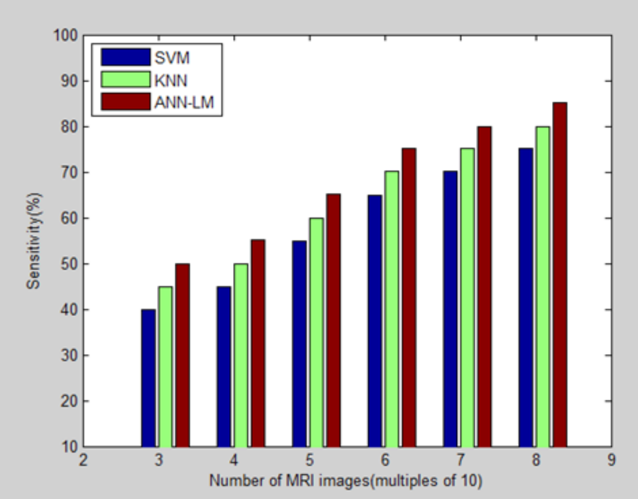

Figure 5. Comparison of sensitivity rate of proposed and existing system classifiers.

$$Sensitiity = \frac{TP}{(TP + FN)} * 100 \quad (23)$$

The Figure 5 shown below describes the comparison of sensitivity rate of the proposed method and existing classification methods.

Table 1 presents sensitivity results for the MRI brain image processing obtained using the proposed method classifier and existing techniques. The table values are represented as No. of input images Vs proposed and existing Classification methods, which are used for MRI brain image classification and that indicates the sensitivity obtained for each tenth of the testing stage MRI brain image inputs, which are labeled as DiCom Images (DCI) in Tables 1, 2 and 3.

Table 1. The sensitivity rate (%) of the proposed and existing method

METHOD / Input Images	SVM (%)	KNN (%)	ANNLM (%)
DCI30	39.91	47.32	51.43
DCI40	45.21	48.90	56.91
DCI50	58.44	59.82	67.92
DCI60	66.98	70.15	74.23
DCI70	69.81	73.25	81.48
DCI80	77.47	79.98	87.59

Table 2. The specificity rate (%) of the proposed and existing method

METHOD / No. of Input Images	SVM (%)	KNN (%)	ANNLM (%)
DCI30	40.17	47.54	50.09
DCI40	47.32	49.82	57.08
DCI50	56.54	60.19	67.27
DCI60	65.87	70.41	78.17
DCI70	70.12	74.62	80.11
DCI80	74.87	79.94	85.89

3.1.2 Specificity

Specificity (or) True Negative Rate is the probability of actual negative classes which are identified correctly.

$$Specificity = \frac{TN}{TN + FP} * 100 \quad (24)$$

Table 3. The classification rate comparison of the proposed and existing method

METHOD / No. of Input Images	Without ACM			With ACM		
	SVM (%)	KNN (%)	ANNLM (%)	SVM (%)	KNN (%)	ANNLM (%)
DCI30	32.13	33.5	38.54	40.34	45.26	48.19
DCI40	42.5	45.08	47.52	51.17	57.5	59.23
DCI50	51.89	52.21	59.43	60.18	68.52	71.32
DCI60	63.25	65.18	67.50	69.53	78.51	80.44
DCI70	72.55	75.22	77.64	80.02	87.47	89.32
DCI80	78.96	80.91	83.55	86.50	91.14	93.74

Where, TP (True Positive) is the number of correctly classified Tumor cases,

FP (False Positive) is the number of incorrectly classified Tumor cases,

FN (False Negative) is the number of incorrectly classified Non-Tumourous, and

TN (True Negative) is the number of correctly classified Non-Tumourous.

The Figure 6 shown below describes the comparison of specificity rate of the proposed method and existing classification methods. The Table 2 shows that the specificity rates of the proposed and existing methods.

Table 2 presents specificity results value for the MRI brain image processing which is obtained using the proposed and existing classifiers used in this work. In the table value represents the No. of input images Vs Classification methods. Note that with respect to Table 2. The test dataset comprised each 10 images, thus for each testing phase run all given input images, and final graph result shows that all 80 images were classified correctly. On the other hand, statistical comparison indicates that the ANN-LM classifier provides better sensitivity and specificity value than the existing classifiers for the MRI brain image data set, both the sensitivity and specificity value of the proposed classifier used in this method increased in the rate of (>0.05) in each 10 given input images.

3.1.3 Accuracy

Accuracy is the percentage of correct classification of cases and healthy patients.

$$Accuracy = \frac{(TP + TN)}{(TP + FN + FP + TN)} * 100 \tag{25}$$

The proposed image analysis process consists of two important stages, such as region based ACM segmentation process and ANN-LM classification. For final efficient classification in the MRI image analysis, feature extraction process also considered as one of the important process of this proposed system. Then this proposed MRI image analysis method clearly shows that the final ANN-LM classifier provides the high accuracy results when it is using the segmentation and feature extraction process in the MRI image analysis. Comparing the accuracy results of the classification process of proposed MRI image analysis, the accuracy rate of the analysis process increased

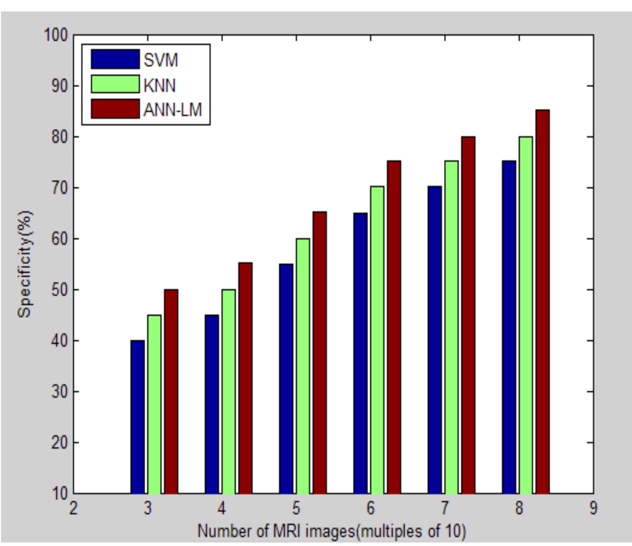

Figure 6. Specificity rate of proposed and existing system classifiers.

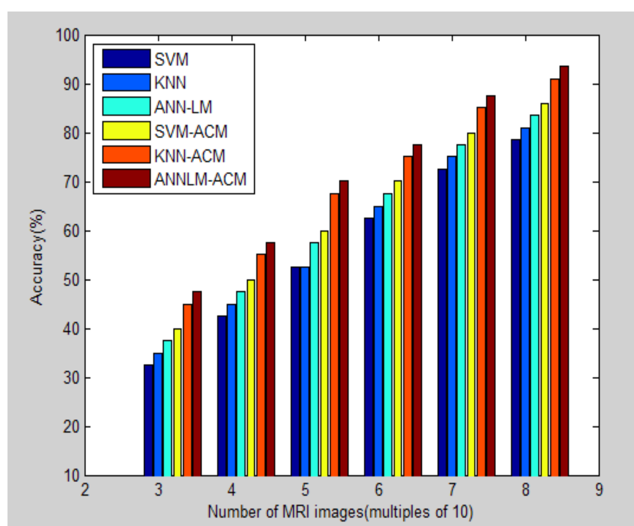

Figure 7. Comparison of accuracy rate of proposed system classifier and existing classification system classifier.

Table 4. Evaluation of proposed method accuracy compare with various classifier approaches in testing data set

Dataset	Evaluation Matrices	SVM	KNN	ANNLM	SVM + ACM	KNN +ACM	ANNLM+ACM
DIOCOM input MRI brain Images (DCI)	TP	10	12	18	23	38	45
	TN	6	9	25	43	24	28
	FP	28	33	13	7	8	3
	FN	36	26	24	7	10	4
	Sensitivity (%)	77.47	79.98	87.59	89.47	86.84	90.98
	Specificity (%)	74.87	79.94	85.89	94.74	89.68	87.47
	Accuracy (%)	78.96	80.91	83.55	86.50	91.14	93.74

when classification process with ACM segmentation and texture and shape feature extraction applying in the proposed MRI image analysis process. However the segmentation and feature extraction processes are the important aspects of the final classification result, which is proposed. The Figure 7 described the accuracy result of the ANN-LM classification process with ACM segmentation, and without segmentation and also it is compare with existing method classifiers. The Figure 7 shows that the comparison of the ACM segmentation process with and without the both existing and proposed classifiers used in this work.

From the Table 1, Table 2 and Table 3 it can be seen that excellent results were obtained throughout. The final classification result shown in Figure 7 proves that the proposed ACM segmentation process improves the ANN-LM classification results in the MRI image analysis process.

The obtained experimental results of the existing and proposed methods are given in Table 4. By analyzing the results, the proposed method has a better performance. The outcomes of the experimentation proved with 94% of accuracy in ANN-LM classifier with ACM segmentation based method with detection of tumours from the brain MRI images. Then this proposed region based ACM segmentation, feature extraction techniques combined with ANN-LM classification in MRI image analysis process efficiently classified the given input MRI brain image dataset as normal and abnormal or Tumourous and non-Tumourous. The Table 3 shows that the comparison classification results value of the proposed and existing methods.

4. Conclusion

This work proposed a new approach for tumour diagnosis in the MRI images. Here, this work shows that robust classification and segmentation with feature extraction methods can be promising a new concept for detecting abnormalities in the brain images. The method was implemented and MRI brain image datasets were utilized to analyze the results of the ANN with LM classification method. The performance analysis of classifier with ACM segmentation proved that the proposed method offers high accuracy, and sensitivity, specificity measures, respectively.

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