Automated Brain Tumor Detection and Identification Using Image Processing

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Abstract: In this paper, modified image segmentation techniques were applied on MRI scan images in order to detect brain tumors. Also in this paper, a modified Probabilistic Neural Network (PNN) model that is based on learning vector quantization (LVQ) with image and data analysis and manipulation techniques is proposed to carry out an automated brain tumor classification using MRI-scans. The assessment of the modified PNN classifier performance is measured in terms of the training performance, classification accuracies and computational time. The simulation results showed that the modified PNN gives rapid and accurate classification compared with the image processing and published conventional PNN techniques. Simulation results also showed that the proposed system out performs the corresponding PNN system presented in [30], and successfully handle the process of brain tumor classification in MRI image with 100% accuracy when the spread value is equal to 1. These results also claim that the proposed LVQ-based PNN system decreases the processing time to approximately 79% compared with the conventional PNN which makes it very promising in the field of in-vivo brain tumor detection and identification.

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Introduction:

The National Cancer Institute (NCI) estimated that 22,070 new cases of brain and other central nervous system (CNS) cancers would be diagnosed in the United States in 2009. The American Brain Tumor Association (ABTA) clarifies this statistic further by estimating that 62,930 new cases of primary brain tumors would be diagnosed in 2010 [1-3]. Today, tools and methods to analyze tumors and their behaviour are becoming more prevalent. Clearly, efforts over the past century have yielded real advances; however, we have also come to realize that gains in survival must be enhanced by better diagnosis tools [1, 3]. Although we have yet to cure brain tumors, clear steps forward have been taken toward reaching this ultimate goal, more and more researchers have incorporated measures into clinical trials each advance injects hope to the team of caregivers and, more importantly, to those who live with this diagnosis [1-3]. Magnetic Resonance Imaging (MRI) is the state-of the-art medical imaging technology which allows cross sectional view of the body with unprecedented tissue contrast [4-5]. MRI is an effective tool that provides detailed information about the targeted brain tumor anatomy, which in turn enables effective diagnosis, treatment and monitoring of the disease. Its techniques have been optimized to provide measures of change within and around primary and metastatic brain tumors, including edema, deformation of volume and anatomic features within tumors, etc [6]. MRI provides a digital representation of tissue characteristic that can be obtained in any tissue plane. The images produced by an MRI scanner are best described as slices through the brain. MRI has the added advantage of being able to produce images which slice through the brain in both horizontal and vertical planes. This makes the MRI-scan images an ideal source for detecting; identifying and classifying the right infected regions of the brain. Most of the current conventional diagnosis techniques are based on human experience in interpreting the MRI-scan for judgment; certainly this increases the possibility to false detection and identification of the brain tumor. On the other hand, applying digital image processing ensures the quick and precise detection of the tumor [7]. One of the most effective techniques to extract information from complex medical images that has wide application in medical field is the segmentation process [5, 8]. The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion. Widely used homogeneity criteria include values of intensity, texture, color, range, surface normal and surface curvatures. Color based segmentation using K-means clustering for brain tumor detection has been proposed, in which better results were obtained using the developed algorithm than that in other edge detection algorithms [9]. A modified method was proposed that additionally takes into account the symmetry analysis and any significant prior information of the region of interest as well as the region area and edge information in the tumor location of pathological cases [10]. However, all of these research efforts pushed the limit of tumor detection accuracy, they have been based on edge detection and were employed tofilter out less relevant information while preserving the basic structural properties of an image which significantly reduces the amount of data to be processed in the subsequent steps such as feature extraction, image segmentation, registration, and interpretation. This is why with the recent developments. On computational intelligence; the design of computerized medical diagnosis systems has received more and more attention. These reasons motivated us to propose two automated diagnosis systems; the first system is completely based on modified classical image processing algorithms, while the second system is based on probabilistic artificial neural network classifier to interpret medical images obtained from clinical tests.

The rest of the paper is organized as follows. In section II, conventional image segmentation techniques are summarized. The proposed approach that includes image segmentation techniques, filters and a modified edge detection algorithm is presented in section III. The neural network model employed for this research as well as the simulation results are discussed in section IV. Section V presents the paper conclusions and summary.

II. Conventional Image Segmentation Techniques

Image segmentation plays a critical role in all advanced image analysis applications, a key purpose of segmentation is to divide image into regions and objects that correspond to real world objects or areas, and the extent of subdivision depends on requirements of specific application. Complete segmentation of an image scene, where objects correlate with real world objects, cannot be usually achieved without inputs from the user or specific knowledge of the problem domain. Image feature selection is a significant prerequisite for most image processing algorithms, depending on these features the segmentation methods can be classified into three categories namely, thresholding, edge-based, region-based segmentation and classifier such as Hierarchical Self Organizing Map (HSOM) [11-12]. Image thresholding is the most popular segmentation method due to its intuitive properties and simple implementation [11]. Threshold selection plays a very crucial role for efficient segmentation results. Intuitively, the thresholds for multimodal histograms should be the minima between the two maxima. Some techniques sharpen the histogram peaks in image enhancement stage so as to facilitate the threshold detection. The main disadvantage of this method is the difficulty to separate object from background if the object and background are of the same intensity distribution or texture as in MRI-scans. Edge-based segmentation is described in terms of discontinuities in image attributes as Gray level, texture, color etc. These discontinuities are known as edges and are detected using edge detection operators, some of the commonly used operators are Sobel, Prewitt, Laplace, etc [13]. Segmentation resulting from edge-based method cannot be used as partial segmented output due to the presence of broken, stray, or noise edges. Advanced processing is required to obtain edges corresponding to meaningful objects. Several algorithms introduced for edge-based segmentation, the widely accepted segmentation methods are edge-image thresholding which is used to eradicate insignificant edges that occur due to factors such as noise and improper lighting conditions [13]. Edgeimage thresholding leads to stray edges in presence of noise where the actual edges are often missing [11].

Stray edges problem can be solved if the edge properties are determined with respect to the mutual neighbours, while presence of edge is substantiated depending on the strength of edges in local neighbourhood [11]. Region-based segmentation is then used which is based on finding similarity measures to merge and split regions in an image so as to form semantic or useful division in the processed image. Self Organizing Map, SOM, as part of competitive learning neural network (CLNN) has been used to implement the vector quantization process [14-16]. The importance of SOM for vector quantization is primarily due to the similarity between the competitive learning process employed in the SOM and the vector quantization procedure. Neural units in the competitive layer need to be approximately equal to the number of regions desired in the segmented image. It is not however, possible to determine a priori the correct number of regions in the segmented image. This is the main limitation of the conventional SOM for image segmentation. The HSOM directly addresses the aforesaid shortcomings of the SOM. HSOM is the combination of self organization and topographic mapping technique. HSOM combines the idea of regarding the image segmentation process as one of data abstraction where the segmented image is the final domain independent abstraction of the input image [16].

In this paper we integrated the last three approaches and enhanced their accuracy by combining both Gaussian and Canny edge detection filters as discuss in the next sections.

III. Image Processing Proposed Approach and Simulation Results

A. Image Acquisition

In our proposed approach we first considered that the MRI scan images of a given patient are either color, Gray-scale or intensity images herein are displayed with a default size of 220×220. If it is color image, a Gray-scale converted image is defined by using a large matrix whose entries are numerical values between 0 and 255, where 0 corresponds to black and 255 to white for instance. Then the brain tumor detection of a given patient consist of two main stages namely, image segmentation and edge detection.

B. Image Segmentation

The objective of image segmentation is to cluster pixels into prominent image region. In this paper, segmentation of Gray level images is used to provide information such as anatomical structure and identifying the Region of Interest i.e. locate tumor, lesion and other abnormalities. The proposed approach is based on the information of anatomical structure of the healthy parts and compares it with the infected parts. It starts by allocating the anatomical structure of the healthy parts in a reference image of a normal candidate brain scan image as shown in Fig. 1 then it allocates the abnormal parts in the unhealthy patient brain. Scan image by comparing it with the reference image information as shown in Fig. 2.

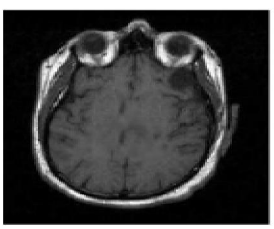

Figure 1: Normal Brain

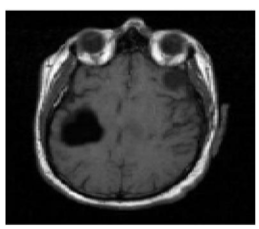

Figure 2: Abnormal Brain

1. Enhancement and Smoothing:

There are different types of noise encountered by different techniques, depending on the noise nature and characteristics, namely Gaussian noise and impulse noise. In this paper we assumed that the main image noise is additive and random; that is spurious and random signal, n(i, j), added to the true pixel value I(i, j):

$$II(i,j) = I(i,j) + n(i,j) \tag{1}$$

In this algorithm the enhancement in spatial domain is based on direct manipulation of pixels in a small neighbourhood of pixels, it generally takes the form;

$$g(x,y) = T[f(x,y)] \tag{2}$$

in which f(x, y) is the input image, g(x, y) is the processed image, and T is an operator on f, defined over some neighbourhood of (x, y). Then we applied the next enhancement in frequency domain which is based on the concept of the convolution theorem and spatial filters. In this paper, the proposed noise enhancement algorithm is based on using spatial filters and includes the following: Smoothing filters that are used to reduce or remove Gaussian noise from the MRI image. Sharpening filters that are used for highlighting edges in an image, and are based on the use of first and second order derivatives.

2. Smoothing by Linear filter:

Linear operations calculate the resulting value in the output image pixel $I_A(i,j)$ as a linear combination of brightness in a local neighbourhood of the pixel I(i,j) in the input image. In this algorithm we assumed I as an N×M image, m is an odd number smaller than both N and M, and A is the convolution kernel or the filter mask of the linear filter that is an m×m mask. The filtered version of I is given by the discrete convolution as follows:

$$I_A(i,j) = \sum_{h-m/2}^{m/2} \sum_{k-m/2}^{m/2} A(h,k) I(i-h, j-k) \tag{3}$$

Where i=1 to N and j=1 to M. This filter replaces the value I(i, j) with a weighted sum of I values in a neighbourhood of (i, j). If all entries of A in Eq. (3) are non-negative, the filter performs average smoothing. Then the matrix of the abnormal brain scan image is subtracted from that of the normal brain image resulting in a matrix of the region of interest accompanied with some noise as illustrated in Fig. 3.

3. Smoothing using Gaussian filter

In this paper, the proposed Gaussian smoothing filter, G_f, is a nonnegative, real-valued column matrix defined by,

$$G_f(x,y) = \frac{1}{c}\exp\left(\frac{-[x^2+y^2]}{2\sigma^2}\right) \tag{4}$$

in which c is expressed as $c = \sqrt{2\pi\sigma^2}$.

However this type of filters enhanced the noise reduction level compared with the linear filters, it was observed that these smoothing and noise filters did not completely satisfy the noise removal level from the original image as shown in Fig. 4. Thus, for these applications a set of cascaded filters are recommended. We therefore proposed another stage of noise filtering by using an average filter.

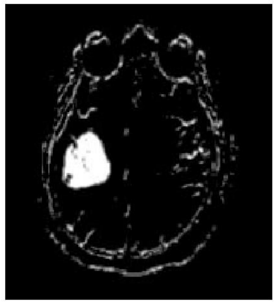

Figure 3: Applying Gaussian filter Figure 4: applying Average Filter

Applying the average filter resulted in an acceptable noise reduction level for such applications. The conclusion from this part is cascaded filter array is recommended to reach an acceptable noise reduction levels brain tumor detection.

C. Edge Detection

An edge is a property attached to an individual pixel and is calculated from the image function behaviour in a neighbourhood of the pixel. It is also considered as a vector variable (magnitude of the gradient, direction of an edge). The purpose of edge detection in general is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for further image processing. In this paper, other than filtering the region of interest (ROI) is proposed to identify different tumor types and/or different infected areas. It also introduced to enhance the processing time by executing the features processing algorithm in the identified areas instead of the whole image frame. In this research, we first applied a vector subtraction algorithm then the ROI is determined by finding the related adjacent portions in the resultant image from the vector subtraction. The area of each related adjacent portion is computed and the irrelevant portions removed resulting in the desired tumor region as shown in Fig. 6.

To enhance the results of the proposed edge detection algorithm we found that the most important criteria that affect the edge detection performance are by reducing the rate error of losing edges in an image and that edge points must be well localized. Therefore, we successfully modeled and implemented Canny's mathematical formulas [17] to increase the performance of the proposed edge detection algorithm. Even though it is quite old, it has become one of the standard edge detection methods and it is still used in research [18].

D. Canny Edge detection

The Canny algorithm can be used an optimal edge detector based on a set of criteria which include finding the most edges by minimizing the error rate, marking edges as closely as possible to the actual edges to maximize localization, and marking edges only once when a single edge exists for minimal response. According to Canny [29], the optimal filter that meets all three criteria above can be efficiently approximated using the first derivative of a Gaussian function in Eq. (4). These derivatives are used to calculate gradient magnitude (edge strength) and gradient direction of most rapid change in intensity.

E. The Modified Canny Edge Detection Algorithm

The algorithm runs in 5 separate steps as shown in Fig. and described as follows

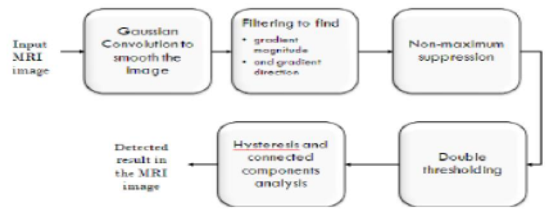

Figure 5: Modified Canny edge detection algorithm

1. Smoothing: Blurring of the image to remove noise. Therefore the image is first smoothed by applying a Gaussian filter. Our proposed method uses 5×5 Gaussian template and the original image to weight neighbourhood. Denote any point (x, y) of the image as the center when processing and extracting 5×5 neighbourhood, the weighting neighbourhood can be indicated as follows:

$$I_A(x,y) = \frac{1}{5\times5}\sum_{i-2}^{2} \quad \sum_{j-2}^{2} I\,(x+i, y+j) \times M(2+i, 2+j) \quad (5)$$

where x=1,2,…,m; y=1,2,…,n , I(x,y) is the pixel value of the original sub-image, M is the Gaussian template, and IA(x,y) is the pixel value of the smoothed image.

2. Finding gradients: The edges should be marked where the gradients of the image has large magnitudes (edge strength). In this step we compute gradient direction and amplitude of smoothed image IA(x,y) adopting first order partial finite difference of 2×2 neighborhood.

$$M(x,y)= \sqrt{g_x^2(x,y) + g_y^2(x,y)} \quad (6)$$

$$\theta = \arctan\left(\frac{g_y(x,y)}{g_x(x,y)}\right) \quad (7)$$

$$\int x = \begin{bmatrix} \frac{-1}{2} & \frac{1}{2} \\ \frac{-1}{2} & \frac{1}{2} \end{bmatrix}, \int y = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \end{bmatrix} \quad (8)$$

where gx and gy are the gradients in the x- and y- directions respectively and represents the results of the original image filtered along rows and lines. θ is the gradient direction.

3. Non-maximum suppression: Only local maxima should be marked as edges. If the gradient amplitude of the pixel is no less than the gradient amplitude between two adjacent pixels in the gradient direction, the point can be judged as the edge point possibly. The purpose of this step is to convert the "blurred" edges in the image of the gradient magnitudes to "sharp" edges. Basically this is done by preserving all local maxima in the gradient image, and deleting everything else. The algorithm is for each pixel in the gradient image.

a. Round the gradient direction θ to nearest 45 ◦ , corresponding to the use of an 8-connected neighbourhood.
b. Compare the edge strength of the current pixel with the edge strength of the pixel in the positive and negative gradient direction. I.e. if the gradient direction is north (θ =90◦), compare with the pixels to the north and south.
c. If the edge strength of the current pixel is largest; preserve the value of the edge strength. If not, suppress (i.e. remove) the value.

4. Double thresholding: Potential edges are determined by thresholding. Edge pixels stronger than the high threshold are marked as strong; edge pixels weaker than the low threshold are suppressed and edge pixels between the two thresholds are marked as weak.
5. Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge. Strong edges are interpreted as "certain edges", and can immediately be included in the final edge image. Weak edges are included if and only if they are connected to strong edges. The logic is of course that noise and other small variations are unlikely to result in a strong edge (with proper adjustment of the threshold levels). Thus strong edges will (almost) only be due to true edges in the original image. The weak edges can either be due to true edges or noise/color variations. The latter type will probably be distributed independently of edges on the entire image, and thus only a small amount will be located adjacent to strong edges. Weak edges due to true edges are much more likely to be connected directly to strong edges. In this paper edge tracking is implemented by iterative BLOB-analysis (Binary Large Object). The edge pixels are divided into connected BLOB's using 8-connected neighbourhood. BLOB's containing at least one strong edge pixel is then preserved, while other BLOB's are suppressed

F. Simulation Results

Proposed algorithm is implemented using MATLAB where the source image and the thresholds can be chosen arbitrarily and the implementation uses the correct Euclidean measure for the edge strengths. Simulation results after applying Canny-based edge detection algorithm on MRI scan images showed the ability of the proposed algorithm to accurately detect and identify the contour of the tumor as shown in Fig. 7.

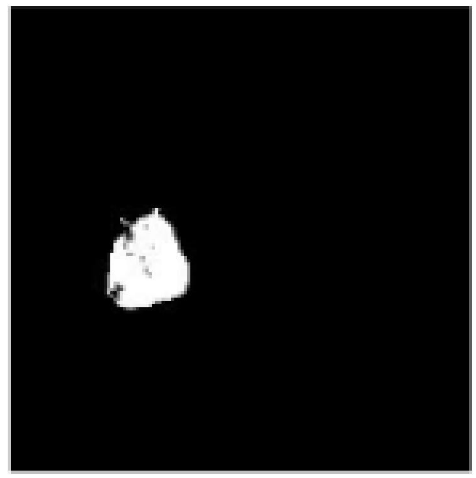

Figure 6: Region of Interest

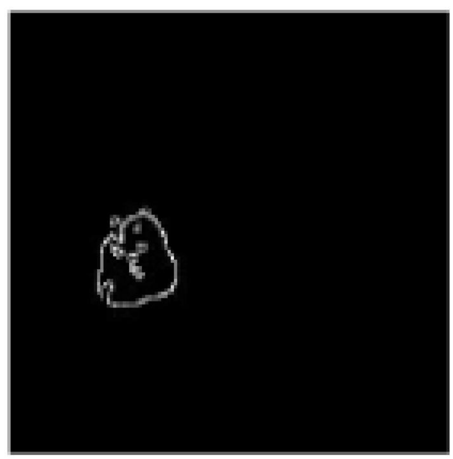

Figure 7: Canny Edge Detection

IV. Probabilistic Neural Network Proposed Approach and Simulation Results

Recently there has been an increase of activities in the application of neural networks to medical imaging [19-26]. The purpose is to make use of the parallel distributed processing nature of neural networks to reduce computing time and enhance the classification accuracy. Applications of neural network to pattern classification have been extensively studied in the past many years. Various kinds of neural-network architecture including multilayer perceptron (MLP) neural network, radial basis function (RBF) neural network, self-organizing map (SOM) neural network, and probabilistic neural network (PNN) have been proposed [19]. An inherent statistical foundation in Bayesian estimation theory and its ease of training make PNN an effective tool for solving many classification problems [20- 26]. However, it requires a very large neural network to analyze an entire image with huge number of interconnected networks and its associated network size, the locations of pattern layer neurons as well as the value of the smoothing parameter. A PNN is predominantly a classifier since it can map any input pattern to a number of classifications. PNN is a fast training process and an inherently parallel structure that is guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining. A consequence of a large network structure is that the classifier tends to be oversensitive to the training data and is likely to exhibit poor generalization capacities to the unseen data [27]. The second problem is related to the smoothing parameter which also plays a crucial role in PNN classifier, and an appropriate smoothing parameter is often data dependent. These two problems have been solved by other researchers such as in [25-27]. In this paper, Probabilistic Neural Network is used to classify a brain tumor in an MRI image according to its proximity to the most relevant training vector. The PNN network consists of three layers respectively: input layer, pattern layer and competitive layer as shown in Fig 8. It is presumed that there are Q input vector/target vector pairs (number of neurons in layer 1) where each target vector has number of classes K (number of neurons in layer 2). One of these elements is 1 and the rest are 0. Thus, each input vector is linked with one of K classes. The transpose of the matrix created from the Q training pairs, P`, determines the first layer input weights, IW1,1. With each input introduced, the ||dist|| box produces a vector whose elements indicate the proximity of the input to the vectors of the training set. These elements are then multiplied, element by element, by the bias and sent to the radbas transfer function given by,

$$\mathrm{radbas}(n) = e^{-n^2} \quad (9)$$

An input vector close to a training vector is represented by a number close to 1 in the output vector a1. If an input is close to several training vectors of a single class, it is represented by several elements of a1 that are close to 1. The matrix T of the target vectors however determines the second-layer weights, IW2,1. Each vector contains a single 1 only in the row associated with that specific class of input, and 0's elsewhere. The multiplication Ta1 then sums the elements of a1 resulting from each of the K input classes. Finally, the second-layer transfer function, compete, produces a 1 corresponding to the largest element of n2, and 0's elsewhere. Thus, the network classifies the input vector into a specific K class since that class has the maximum probability of being correct [29]. A research trial as presented in [30] implemented an automated brain tumor classification system using PNN. Their data set images were divided into 20 training images and 15 testing. The Principle component analysis was applied on MRI images to extract the features of the images. In this research, neither image enhancement nor segmentation was applied.

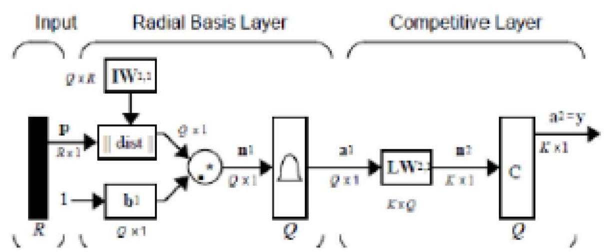

Figure 8: Probabilistic Neural Network Architecture

A. The Proposed System

In this paper, the proposed system is a modified version of the conventional PNN. The modification is based on automatic utilization of specified regions of interest (ROIs) within the tumor area in the MRI images. Form each ROI, set of extracted features include tumor shape and intensity characteristics are extracted and normalized. Each ROI is then given a weight to estimate the PDF of each brain tumor in the MR image. These weights are used as a modeling process to modify the conventional PNN. This method is based on learning vector quantization (LVQ) which is a supervised competitive learning technique that obtains decision boundaries in input space based on training sets to reduce the size of the hidden layer. It defines class boundaries prototypes, a nearest-neighbour rule and a winner-takes-it-all paradigm LVQ is composed of three layers: input layer, competitive layer and output layer. The input data is classified in the competitive layer and those classes or patterns are mapped to target class in the output layer. In the learning phase weights of neurons are adjusted based on training data. The winner neuron is calculated based on the Euclidean distance, and then the weight of the winner neuron is adjusted.

B. Methodology

There are four major steps in the proposed approach for brain tumor classification. The first step is ROI segmentation in which the boundary of the tumor (ROI) in an MR image is identified; the second step is the feature extraction of the meaningful features of the ROI; the third step is the feature selection; the last step is the classification process in which learning a classification model using the features. The proposed algorithm starts by reading the input image, converting it to grey scale image then applying image segmentation techniques for extracting the Region of Interest (ROI). A set of reference MRIs is taken as the training database. Feature vectors are extracted for each image in the training set during the training phase. In the testing phase, the feature vector of the test image is computed. Figure 9 illustrates the sequence of the proposed approach. The proposed approach is evaluated on real images, and the results are compared with other algorithms, in particular conventional PNN algorithm presented by [30]. During the segmentation process, each image region confined by a rectangular window is represented by a feature vector of length R. These vectors computed for Q selected regions are organized in the pattern matrix PR,Q and form clusters in the R-dimensional space. The Q pattern vectors in P are fed into the input NN layer, while the number C of the output layer elements represents the desired number of segmentation classes [31].

The algorithm comprises of the following successive steps:

1. Feature vectors computation to create the feature matrix P using the sliding window.
2. Initialization of the learning process coefficients and the network weights matrix W.
3. Iterative application of the competitive process and the Kohonen learning rule [32] for all feature vectors during the learning stage.
4. NN simulation to assign class numbers to individual feature vectors.
5. Evaluation of the regions classification results.

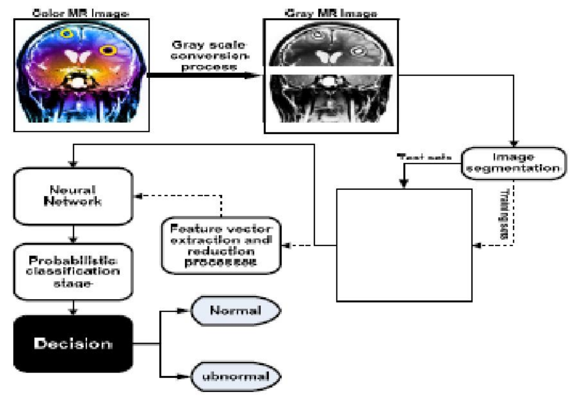

Figure 9: The Proposed PNN-Based Brain Tumor Classification System

C. Model learning

Probabilistic Neural Networks (PNN) is a supervised feed forward networks derived from Bayesian Decision Networks. Typically PNN is built with four layers. Training and testing vectors are normalized prior to input into the network. First layer consists of neurons for each input feature. The second layer has one neuron (Pattern unit) for each pattern in the training dataset. Each neuron in the pattern unit computes the dot product of training pattern and testing pattern then performs Gaussian transformation. The proposed architecture for PNN is based on using f-mean instead of dot product of training pattern with the testing pattern, which results in reduced computational time to classify an unknown pattern. The modified PNN comprises only three layers instead of four. First layer consists of neurons for each input feature. The second layer has one neuron for each class of the training dataset. Each neuron in the second layer computes the f-mean between input vector and the weight vector. The third layer is the decision layer which compares values passed from the neurons of second layer. The neuron of the second layer at which maximum value occurs decides the class of the input pattern. In conventional probabilistic neural network, the entire training set must be stored and used during testing and the amount of computation necessary to classify an unknown point is proportional to the size of the training set. But in the modified PNN, second layer contains one neuron for each class of the training dataset leading to much less computational time for classification. A three layer neural network was created with 500 nodes in the first (input) layer, 1 to 50 nodes in the hidden layer, and 1 node as the output layer. We varied the number of nodes in the hidden layer in a simulation in order to determine the optimal number of hidden nodes. But in the final simulation experiment we elected only ten nodes in the hidden layer. The 500 data points extracted from each subject were then used as inputs of the neural networks. The output node resulted in either a 0 or 1, for control or patient data respectively. The weights in the hidden node needed to be set using training sets. Therefore, subjects were divided into training and testing datasets.

D. Experimental Results

A set of MRI-scan Gray-scale image database was used in this experiment each image size is 220×220 pixels. A group of 64 MRI images were used that were categorized into 6 classes respectively. Out of the 64 subjects a group of 18 random patients MRI images were selected as a test set, while the rest of the dataset was used for training. Training data was used to feed into the neural networks as inputs and then knowing the output, the weights of the hidden nodes were calculated. Many trials were performed on the same Neural Network, selecting 18 subjects randomly every time for testing and the remaining subjects for retraining to find accuracy of neural network prediction. Table I shows the network performance results compared with the results presented in [30]. The results presented in this table show that the proposed system out perform the presented system in [30], and successfully handle the process of MRI image classification with 100% accuracy when the spread value is equal to 1. It is also noted that the proposed LVQ-based PNN system decreased the processing time to approximately 79% compared with the conventional PNN.

TABLE I
COMPARISON OF THE CLASSIFICATION PERFORMANCE USING OUR PROPOSED MODEL WITH THAT PRESENTED IN [30].

	Results presented in [30]	Our proposed system
Number of training Images	20	64
Number of testing Images	15	18
Spread Value	1	1
Network performance for correct images	73%	100%

V. CONCLUSION

In this paper, we proposed two approaches for Brain tumor detection, identification and classification. The first approach is based on an integrated set of image processing algorithms, while the other is based on a modified and improved probabilistic artificial neural networks structure. The proposed integrated image processing algorithm is based on a modified Canny edge detection algorithm and implemented using MATLAB. However, simulation results using this algorithm showed its ability to accurately detect and identify the contour of the tumor, its computational time and accuracy were much less than its corresponding algorithms that use the parallel distributed processing nature of neural networks to reduce computing time and enhance the classification accuracy. This leaded us to propose a modified and improved probabilistic artificial neural networks structure. The modification is based on automatic utilization of specified regions of interest (ROIs) within the tumor area in the MRI images. Form each ROI, set of extracted features include tumor shape and intensity characteristics are extracted and normalized. Each ROI is then given a weight to estimate the PDF of each brain tumor in the MR image. These weights are used as a modeling process to modify the conventional PNN. This method is based on learning vector quantization (LVQ) which is a supervised competitive learning technique. This model is successfully tested by using a set of infected brain MRI-scan images to classify brain tumor. In our experiments, a database of 64 MRI-scan Gray-scale image was used, each image size is 220×220 pixels. Out of the 64 subjects a group of 18 random patients MRI images were selected as a test set, while the rest of the dataset was used for training. Training data was used to feed into the neural networks as inputs and then knowing the output, the weights of the hidden nodes were calculated. Many trials were performed on the same Neural Network, selecting 18 subjects randomly every time for testing and the remaining subjects for retraining to find accuracy of neural network prediction. Simulation results showed that the proposed system out perform the presented system in [30], and successfully handle the process of MRI image classification with 100% accuracy when the spread value is equal to 1. It was also concluded that the proposed LVQ-based PNN system decreased the processing time to approximately 79% compared with the conventional PNN and despite considerable progress in probabilistic neural networks, there has been a room for improvement as far as network structure determination is concerned.

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