Combining Tissue Segmentation and Neural Network for Brain Tumor Detection

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Abstract: *The decisive plan in a large number of image processing applications is to take out the significant features from image data, in which a description, interpretation, or understanding of the scene can be provided by the machine. The segmentation of brain tumor from Magnetic Resonance (MR) images is a vital, but time-consuming task performed by medical experts. In this paper, we have presented an effective brain tumor detection technique based on Neural Network (NN) and our previously designed brain tissue segmentation. This technique hits the target with the aid of the following major steps, which includes: Pre-processing of the brain images., segmentation of pathological tissues (Tumor), normal tissues (White Matter (WM) and Gray Matter (GM)) and fluid (Cerebrospinal Fluid (CSF)), extraction of the relevant features from each segmented tissues and classification of the tumor images with NN. As well, the experimental results and analysis is evaluated by means of Quality Rate (QR) with normal and the abnormal Magnetic Resonance Imaging (MRI) images. The performance of the proposed technique is been validated and compared with the standard evaluation metrics such as sensitivity, specificity and accuracy values for NN, K-NN classification and bayesian classification techniques. The obtained results depicts that the classification results yields better results in NNs when compared with the other techniques.*

Keywords: *Brain MRI image, CSF, WM, GM, tumor region, feature extraction, NN.*

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1. Introduction

Magnetic Resonance Imaging (MRI) is a medical imaging technique mostly utilized in Radiology in order to, visualize the structure and function of the human body. It produces the very detailed images of the body in any direction. Particularly, MRI is useful in neurological (brain), musculoskeletal, and oncological (cancer) imaging because it offers much greater contrast between the diverse soft tissues of the body than the Computer Tomography (CT). MRI is different from CT; it does not use ionizing radiation, but uses an effective magnetic field to line up the nuclear magnetization of hydrogen atoms in water in the body [16]. Several current problems in image-guided surgery, therapy evaluation and diagnostic tools greatly benefit from precise 3D models of anatomical structures. This indicates that automated or semi-automated segmentation techniques give considerable importance to the efficient use of medical imagery in clinical and surgical settings. Normally, segmentation involves the separation of anatomical structures from images obtained using modalities such as CT, X-ray, MRI, Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT) or ultrasound, with a main aim of providing exact representations of key anatomical structures, to be used for: Quantitative studies correlating volumes of anatomical structures with pathological or normal development [24, 34] or for 3D visualization of for pre-and intra-operative surgical planning [2, 12].

Most research in developed countries has exposed that the death rate of people affected by brain tumor has increased over the past three decades [21]. Today, one of the major causes for the increase in fatality among children and adults is brain tumor. A tumor is a group of tissue that grows beyond the control of the normal forces that regulates growth. The complex brain tumors can be divided into two main categories based on the tumors origin, their growth pattern and malignancy. Primary brain tumors are tumors that occur from cells in the brain or from the covering of the brain, whereas a secondary or metastatic brain tumor arise when cancer cells spread to the brain from a primary cancer in another portion of the body [25]. The process of segmenting the tumors in MRI images is mainly a challenging and time consuming task. Mostly, the tumors differ greatly in size and position, have a large difference in shape and appearance properties, have intensities overlapping with normal brain tissues, and often a growing tumor can deflect and distort nearby structures in the brain giving an abnormal geometry also for healthy tissue [27].

Identification and segmentation of brain tumor in Magnetic Resonance (MR) images is very crucial in medical diagnosis because it gives information related to anatomical structures as well as potential abnormal tissues necessary for treatment planning and patient follow-up. Precise segmentation of brain tumor is also useful for general modeling of pathological brains as well as the creation of pathological brain atlases [22, 36]. Although, numerous efforts and promising results are obtained in the medical imaging area, precise and reproducible segmentation and classification of abnormalities are still a challenging and complicated task because of the different shapes, locations and image intensities of different types of tumors. Some of them may distort the nearby structures or may be related to edema or necrosis that changes the image intensity around the tumor. Existing techniques leave significant room for increased automation, applicability and precision [18]. Mostly, traditional treatments based on clearly visible tumor leave large parts of brain tissue untreated, which leading to faster tumor reappearance and spread, and decrease the chance of survival [6].

Segmentation of images is an important process in the field of image processing [8]. Normally, it becomes very crucial when coping with medical images where pre-surgery and post-surgery decisions are required for initiating and hastening the recovery process. Generally, the computer aided recognition of abnormal growth of tissues is inspired by the necessity of achieving higher accuracy. Manual segmentation of these abnormal tissues cannot be compared with the current high speed computing machines that allow us to visually observe the size and position of the superfluous tissues. An automatic technique has been developed for the segmentation of brain tumor from MR images [11]. In this paper, we have presented an efficient detection technique for the tumor region in the brain MRI images. Here, we have utilized the brain tissue segmentation technique that we have proposed in our previous research paper [31, 32] we have detected the tumor region with the aid of the region props algorithm [29]. Subsequently, the features vectors of all the segmented regions of the brain MRI image. Then, the abnormality classification is carried out by means of the Neural Network (NN).

The main contribution of this research paper includes:

- Designing of an efficient NN based technique for tumor detection in brain MRI images.
- Segmentation of brain tissues like Cerebrospinal Fluid (CSF), White Matter (WM), Gray Matter (GM) along with the tumor region using our previous approach.
- Extraction of the feature vectors like mean, variance, entropy and wavelet based energy sub-bands of the segmented regions.
- Train the feature vectors using the feed forward NN.
- Efficiency is analyzed by means of the Quality Rate (QR), sensitivity, specificity and the accuracy value.
- Comparison is effectively made with the classification techniques such as NN, K-NN classification and the Bayesian classification.

The rest of this paper is organized as follows: A brief review of researches relevant to the brain tumor detection and segmentation technique is presented in section 2. The proposed brain tumor detection using NN technique is presented in section 3. The detailed experimental results and discussions are given in section 4. The conclusions are summed up in section 5.

2. Related Works

A plentiful of researches has been proposed by researchers for the MRI brain image segmentation and tumor detection techniques. A brief review of some of the recent researches is presented here.

Brain tumor is one of the most dangerous diseases occurring commonly among human beings, so study of brain tumor is very crucial. Bhattacharyya and Kim [5] have proposed an image segmentation technique to identify the tumor from the brain MRI. Several existing thresholding techniques have produced different result in each image. Thus, to produce a satisfactory result on brain tumor images, they have proposed a technique, where the detection of tumor was done uniquely. As well, Badran *et al.* [3] have proposed a computer-based technique for identifying the tumor region accurately in the brain via MRI images. Here, the classification has been performed on a brain tumor image for identifying whether the tumor is a benign or malignant one. The steps involved in the proposed algorithm were preprocessing, image segmentation, feature extraction and image classification via NN techniques. Finally, using the region of interest technique, the tumor area has been located. Their proposed algorithm has been tested using a user friendly Matlab GUI program.

Kharrat *et al.* [17] have developed a methodology, where the brain tumor has been detected from the cerebral MRI images. The methodology includes three stages: Enhancement, segmentation and classification. An enhancement process has been performed to enhance the quality of images as well as to reduce the risk of distinct regions fusion in the segmentation stage. Also, a mathematical morphology has been used to increase the contrast in MRI images. Then, the MRI images have been decomposed by applying a wavelet transform in the segmentation process. Finally, the suspicious regions or tumors have been extracted by using a k-means algorithm. The feasibility and the performance of the proposed technique have been revealed from their experimental results on brain images.

Koley and Majumder [19] have presented a Cohesion based Self Merging (CSM) algorithm for the segmentation of brain MRI in order to find the exact region of brain tumor. CSM has drawn much attention because it gives a satisfactory result when compared to other merging processes. Here, the effect of noise has been reduced greatly and found that the chance of obtaining the exact region of tumor was more and the computation time was very less. Their algorithm was much simpler and computationally less complex.

Identification of brain tumors from MRI is a time consuming and challenging task, because of its variance in shape, size and appearance. Chandra *et al.* [7] have proposed a Particle Swarm Optimization

(PSO) based clustering algorithm. The proposed algorithm has identified the centroids of number of clusters, where each cluster has grouped together the brain tumor patterns, obtained from MR Images. The results obtained for three performance measures have been compared with those obtained from Support Vector Machine (SVM) and Ada Boost. The performance analysis has shown that the qualitative results of proposed model are analogous with those obtained by SVM. Moreover, the different values of PSO control parameters have been selected in order to, acquire better results from the algorithm.

Some years back, the fatality rate by the brain tumor was very high. But, in the recent years, this rate is greatly decreased due to the earlier diagnosis and proper therapy. Today, there are more chances for the long survival of the patient because of the earlier and accurate brain tumor diagnosis. Ain *et al.* [1] have proposed a robust system for brain tumor diagnosis as well as for brain tumor region extraction. Initially, the proposed system has diagnosed the tumor from the brain MR images by naive bayes classification. After the diagnosis, the K-means clustering and boundary detection techniques have been applied to extract the exact brain tumor region. Here, above 99% accuracy has been achieved for diagnosis. Experimental results have shown that the proposed system has extracted accurate tumor region. Their technique has been tested using the datasets of different patients gathered from Holy Family hospice and Abrar MRI and CT Scan center, Rawalpindi.

Khotanlou *et al.* [18] have proposed a technique for segmenting the brain tumors in 3D MR images. Their technique was suitable to different kinds of tumors. Initially, the brain has been segmented using the proposed approach. Then, the suspicious areas have been selected with respect to the approximate brain symmetry plane and fuzzy classification for tumor detection. Here, in the segmentation stage, the tumor has been segmented successfully using the combination of a deformable model and spatial relations. Vagueness and variability have also been considered at all levels using the suitable fuzzy models. Finally, the results obtained on diverse types of tumors have been compared with the manual segmentation results.

Mishra [23] has developed an efficient system, where the brain tumor has been diagnosed with higher accuracy using artificial NN. After the extraction of features from MRI data by means of the wavelet packets, an artificial NN has been employed to find out the normal and abnormal spectra. Normally, the benefit of wavelet packets is that it gives richest analysis when compared with the wavelet transforms and thus adding more advantages to the performance of their proposed system. Moreover, two cancer detection approaches have been discussed. The NN system has been trained using the Error Back Propagation Training Learning rule.

3. Proposed Technique for Tumor Detection in Brain MR Images

Segmentation of medical imagery is a difficult challenge because of the intricacy of the images, as well as the lack of models of the anatomy that entirely capture the possible deformations in each structure. Mainly, the structure of brain is complex, and so its segmentation is an essential step for several problems, especially studies in temporal change detection of morphology, and 3D visualizations for surgical planning [15]. Generally, the problem of image segmentation involves clustering of analogous feature vectors [38, 39]. Thus, extraction of good features is vital for efficient image segmentation. The segmentation task becomes more problematic when one desires to derive common decision boundaries on diverse object types in a set of images. Due to the intricate structure of diverse tissues namely, WM, GM and CSF in the brain images, extraction of useful feature is an essential task. In addition, today the brain tissue and tumor segmentation in MR images is an attractive area of research [4, 9, 14], The block diagram of the proposed technique as shown in Figure 1.

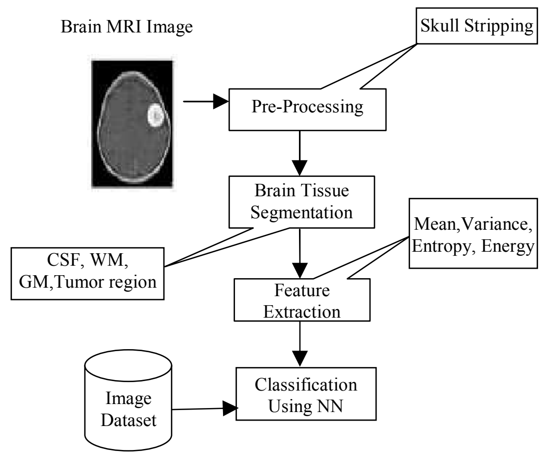


Figure 1. Block diagram of the proposed technique.

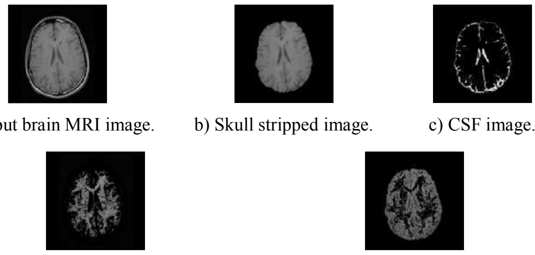
3.1. Techniques for Segmentation of Brain Tissues

Segmentation of brain tissues in MRI image is an important problem in biomedicine that involves number of applications such as diagnosis, surgical planning and monitoring treatment. The major task in brain MRI segmentation is the classification of volumetric data into GM, WM and CSF tissue types. But, it is not easy as it sounds. There are some inbuilt difficulties regarding image segmentation; among them are RF coil in homogeneity, brain tissue vulnerability, and other systematic artifacts. Several preprocessing steps have been presented to tackle some or all of these difficulties. The first processing step in the segmentation of brain tissues is skull stripping. The skull removed MRI images are employed for further classification of the brain tissues into WM, GM and

CSF. The following are the steps involved in the proposed methodology for brain MRI segmentation:

- Skull Stripping.
- CSF Segmentation.
- GM and WM Segmentation.

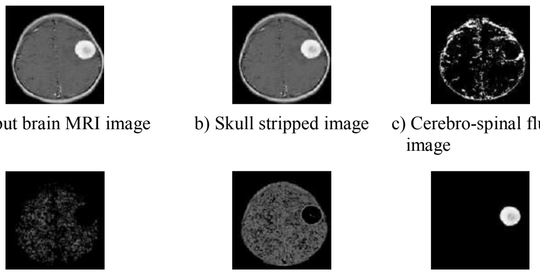
The obtained experimented results by the proposed technique are given as follows in Figure 2 and 3. Here, we have given all the outcomes of the input image with tumor and without tumor region.



a) Input brain MRI image. b) Skull stripped image. c) CSF image.

d) WM. e) GM.

Figure 2. Segmented results of brain MRI without tumor.



a) Input brain MRI image b) Skull stripped image c) Cerebro-spinal fluid image

d) WM. e) GM. f) Tumor region.

Figure 3. Segmented results of brain MRI with tumor.

- *Skull Stripping*: One of the salient pre-processing steps in analyzing intracranial volumes is the extraction of the brain cortex from T1-weighted MRI head scans. The subsequent analysis, tissue segmentation is greatly reliant on the robustness and accuracy of the brain masks generated in the brain extraction phase. By exactly defining the brain cortex, one could essentially reduce the errors for the analyses that follow. In the proposed technique for skull stripping, we noticed that the brain surface is a smooth manifold with relatively low curvature that separates the brain from non-brain regions. Also, the brain cortex can be visualized as a separate dark ring surrounding the brain tissues in the T1 weighted axial MR images. The steps involved in the proposed technique for skull stripping are:
    - Binarization via Thresholding.
    - Morphological Operators.
    - Region-Based Binary Mask Extraction.
- *Binarization via Thresholding*: In binarization, the grey-level image is converted into a binary image. Here, the grey-level value of each pixel in the enhanced image is calculated, and, if the value is above the global threshold, then the pixel value is set to a binary value one; or else, it is set to zero.

$$I = \begin{cases} imbinary\,(i,j) = 0; & if\ I(i,j) < Thres \\ imbinary\,(i,j) = 1; & otherwise \end{cases} \tag{1}$$

- *Morphological Operators*: The binary morphological operators are then applied on the binarized image. The main function of the morphological operators is to remove hurdle and noise from the image. The morphological operators such as opening, closing, erosion and dilation are used in the proposed technique.
- *Opening*: An opening operation involves an erosion followed by dilation with the same structuring element, $I' = imopen(I, S)$.
- *Closing*: A closing operation consists of a dilation followed by an erosion with the same structuring element, $I' = imclose(I, S)$.
- *Erosion*: In the erosion operation on an image I having labels 0 and 1 with structuring element S, the value of pixel i in I is changed from 1 to 0, if the result of convolving S with I, centered at i, is below some predefined value. We have set this value to be the area of S, which is basically the number of pixels that are 1 in the structuring element itself. The structuring element, also called as the erosion kernel, determines the details of how particular erosion thins boundaries, $I' = imerode(I, S)$.
- *Dilation*: Dual to erosion, a dilation operation on an image I' having labels 0 and 1 with a structuring element S, changes the value of pixel i in I from 0 to 1, if the result of convolving S with I', centered at i, is above some predefined value. We have set this value to be zero. The structuring element, also called as the dilation kernel, determines the details of how a particular dilation grows boundaries in an image, $I'' = imdilate(I', S)$.
- *Region-based Binary Mask Extraction*: Region-based extraction is performed by considering the properties of each block that satisfy some criteria. We have utilized one of two criteria. One criterion is to determine the max-min difference and the other is to find out the mean values of the blocks. Subsequently, the process results with a brain mask is applied to the original MRI data. Thus, we have obtained a brain MRI image with its brain cortex stripped.
- *Segmentation of CSF*: The next step after the skull stripping process is to segment the brain into its constituent tissues namely, WM, GM and CSF. The following are the processes involved in the segmentation of CSF and internal brain nuclei.
- *CSF Segmentation*: Regarding CSF segmentation, we assume that there exists some contrast between brain tissue (GM and WM) and CSF, which separates the brain from the extra-cranial tissue. The segmentation techniques are generally grouped into two categories namely, intensity based and surface based. Our technique is an intensity based technique and it does simple thresholding.

In order to, segment the CSF from the brain MRI image, an orthogonal polynomial transform is applied to the skull stripped image. Before the transformation, the image S is blended using the following formula:

$$S' = Sin\left(\frac{S_{(i)}^{\;3}}{100}\right)^2 + (0.05 * rand(|\ S\ |)) \tag{2}$$

- *Orthogonal Polynomial Transform*: Let $(p_l \mid l \geq 0)$ be a series of orthogonal polynomials on I with respect to some weight function $w(x)$, and let μ_l be defined [13, 35]. Let, β_l be the leading coefficient of p_l. We select a value $m \geq 0$, and define $c_m = \beta_{m-1} / (\beta_m \mu_{m-1})$. Then, the following equation holds [28]:

$$\sum_{0 \le l < m} \frac{1}{\mu_l} p_l(x)p_l(y) = \begin{cases} c_m \dfrac{p_{m-1}(y)p_m(x) - p_m(y)p_{m-1}(x)}{x-y}, & x \neq y, \\ c_m\left(p_{m-1}(x)p'_m(x) - p_m(x)p'_{m-1}(x)\right), & x = y, \end{cases} \tag{3}$$

Where, p'_l indicates the derivative of p_l. After applying the polynomial transform, the region related to the CSF are segmented in the resultant image.

- *WM and GM Segmentation*: After the CSF segmentation process, the next step is the segmentation of WM and GM present in the brain MRI. Here, the input to the process is the skull stripped image. The major steps that are followed to segment the GM and WM are explained below.
- The input skull stripped image S is smoothened by using a 2D Gaussian convolution filter to obtain another mage s_I.

Then, x and y gradients of the smoothened image are calculated. The gradient of two variables x and y is defined by:

$$\nabla f\ (x\ ,y\ ) = \frac{\partial f}{\partial x}\hat{i} + \frac{\partial f}{\partial y}\hat{j} \tag{4}$$

The edges present in the image are marked using the gradient values, which as shown in below equations:

$$F = x_{(i)}^{\;2} + y_{(i)}^{\;2} \tag{5}$$

$$E_I = \frac{1}{1+F} \tag{6}$$

Then, the image E_I with the edges marked is subjected to binarization. In the binarization process, the grey-level value of each pixel in the enhanced image is calculated via global threshold T. The global threshold T is determined using the function,

$$T = G_{Th}(E_I) \tag{7}$$

Then, the binarized image BI is given to the binary morphological operators such as *opening* and *closing*. Mainly, the morphological operators are used for the purpose of eliminating any of the hurdles and noises from the image.

Lastly, the WM and the GM issues in the brain MRI are segmented (thresholding) according to their intensity values.

$$R_{out} = \begin{Bmatrix} WM\ ; & BI_i = 1 \\ GM\ ; & BI_i = 0 \end{Bmatrix} \tag{8}$$

- *Tumor Region Segmentation*: Here, the tumor region is identified by means of a Region props algorithm. The regions of the tumor are marked out based on their area properties. The region props algorithm measures the properties of image regions. With the aid of the actual number of pixels in the region, the tumor region's area is segmented. This value is slightly different from the value returned by bwarea, which weights diverse patterns of pixels in a different way. The region props calculate the area by measuring the distance between each neighboring pair of pixels around the border of the region [20].

3.2. Feature Extraction from the Segmented Images

The function of feature extraction is to reduce the original dataset by evaluating some specific properties or features that differentiate one input pattern from another. The extracted features provide the characteristics of the input type to the classifier by considering the depiction of the significant properties of the image [33]. The analyzing methods have been done so far has used the values of pixels intensities, pixels coordinates and some other statistic features namely mean, variance or median, which have much error in determination process and low precision and efficiency in classification [26].

Here, the statistic features we have chosen are Mean M, Variance σ^2, Entropy E and Energy $E(H,\ V,\ D)$ functions. The feature extraction process is carried out by with some initial pre-processing. Each tissue segmented image is split into a limited number of blocks and the feature values are calculated for every block. The block diagram of the feature extraction process is given in Figure 4. The initial steps are as follows:

1. Find the neighbor blocks of the entire divided blocks.
2. Find the distance between all the neighbor blocks.
3. Find the feature values of the blocks with distinct distance measure.
4. Find the average value of all the computed blocks' distance.
5. Store all the features in a vector and fed as an input to the classifier.

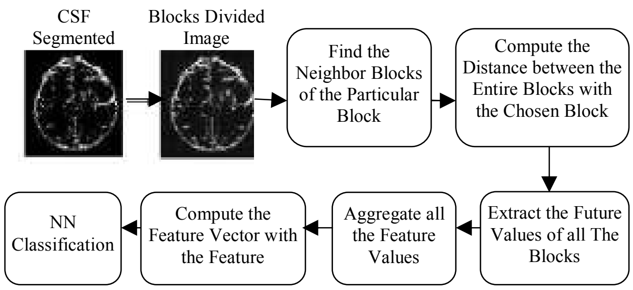


Figure 4. Block diagram of the feature extraction process.

Features can be extracted from the matrix to reduce feature space dimensionality and the formal definitions of chosen features from the matrix are done. The statistic feature's formula is depicted as below:

- *Mean* (*M*): The mean is defined as the sum of the pixel values divided by the total number of pixels values.

$$M = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} x(i, j) \tag{9}$$

- *Variance* (σ^2): The variance is a parameter describing in part either the actual probability distribution of an observed population of numbers, or the theoretical probability distribution of a not-fully-observed population of numbers.

$$\sigma^2 = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (x(i, j) - M)^2 \tag{10}$$

- *Entropy* (*E*): Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as.

$$E = -\sum_i \sum_j x(i, j) \log x(i, j) \tag{11}$$

- *Wavelet based Energy Function* (*E(H, V, D)*: The feature vectors of the three energy functions of high frequency horizontal, vertical and diagonal sub-bands of the wavelet transform are extracted, since it reflects the texture properties.

$$E(H, V, D) = \sum_i \sum_j x(i, j)^2 \tag{12}$$

Feature selection concerns the reduction of the dimensionality of the pattern space and the identification of features that contain most of the essential information needed for discerning between normal and abnormal images. Selection of efficient features can reduce significantly the difficulty of the classifier design. The obtained trained feature is compared with the test sample feature obtained and classified as one of the extracted features. The training Feature Vector F_v is defined by combining all the extracted features like M, σ^2, E and the $E(H,V,D)$. In order to, obtain the three wavelet energies, the Haar wavelet transform is applied to each blocks of brain MRI image. After a one level wavelet transform, a 4×4 pixel block is decomposed into four frequency bands of 2×2 coefficients. For example, the coefficients in horizontal band of one block are *H1*, *H2*, *H3*, *H4*, in vertical band *V1*, *V2*, *V3*, *V4* and in diagonal band *D1*, *D2*, *D3* and *D4*. Then, Horizontal Energy E_H, Vertical Energy E_V and Diagonal Energy E_D are combined to attain the feature value of the energy.

$$F_v = [f(M), f(\sigma^2), f(E), f(E_H), f(E_V), f(E_D)]$$

3.3. MRI Image Classification using Neural Network

As the F_v are extracted, a suitable classifier must be chosen. A number of classifiers are used and each classifier is found suitable to classify a particular kind of F_v depending upon their characteristics. The classifiers we have used here is Feed Forward Neural Network (FFNN). The FFNN was the first and arguably simplest type of artificial NN devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. Here, the network consisted of an input layer of 24 neurons, 1hidden layer with 5 neurons, and an output layer with 1 output neuron, one for each channel.

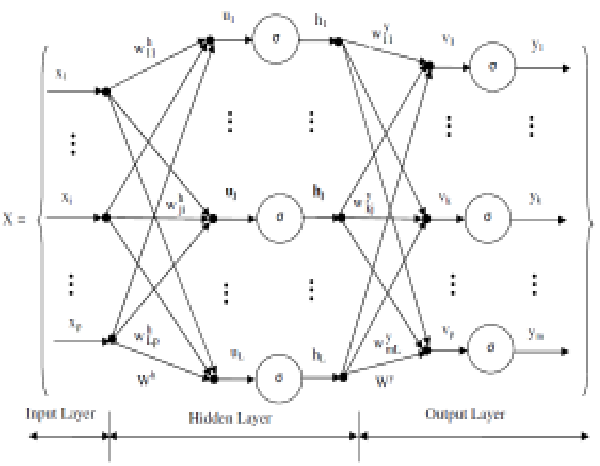


Figure 5. Structure of MLPN.

Literature analysis reveals a persistent application of FFNNs from the different categories of connections for artificial neurons [30]. In FFNN, the neurons of the initial layer drive their output to the neurons of the second layer in a unidirectional mode (i.e., the neurons are not received from the reverse direction). Multilayer Perceptron Neural Networks (MLPNN) or Multilayer Feed-forward Neural Network (MFNN) is one such FNN mechanism. A general structure of MLPNN comprising three layers is portrayed in Figure 5.

The only task of the neurons in the input layer is the sharing of the input signal x_i to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum, given by:

$$y_j = f(\sum W_{ji} X_i) \tag{13}$$

Here, f can be a simple threshold function such as a sigmoid, or a hyperbolic tangent function. The output of neurons in the output layer is calculated in the same way. Following this calculation, a learning algorithm is used in adjusting the strengths of the connections so as to allow a network to achieve a desired overall behavior.

Using this NN, the abnormality of the brain image is been detected. We have given all the computed features values as the input for training the NN with normal and abnormal brain MRI images. In order to, evaluate the classification efficiency, two metrics have been computed:

a) The training performance (i.e. the proportion of cases which are correctly classified in the training process).
b) The testing performance (i.e. the proportion of cases which are correctly classified in the testing process).

Basically, the testing performance provides the final check of the NN classification efficiency, and thus is interpreted as the diagnosis accuracy using the NNs support. Remember that the testing performance, corresponding to the NN based diagnosis accuracy, involves only cases with unknown diagnosis for the NN classifier.

4. Results and Discussion

This section describes the experimental results of our proposed tumor detection technique using different brain MRI images. The proposed technique is implemented in MATLAB (matlab version 7.10). Here, we have tested our proposed tissue segmentation and tumor detection technique using brain MRI images taken from the publicly available sources. The performance of the proposed technique is compared with the different classification techniques such as K-NN classification, NN and the Bayesian classification in order to evaluate the sensitivity, specificity and accuracy.

4.1. MRI Image Dataset Description

The brain MR Image dataset that we have utilized in our proposed tumor detection technique is taken from the publicly available sources. This brain image dataset contains 20 brain MRI images with 10 images with tumor and 10 images without tumor. The brain tumor image dataset are divided into two sets such as, training dataset, testing dataset. The training dataset is used to detect the brain tumor images and the testing dataset is used to analyze the performance of the proposed technique. Here, we have taken the 14 images for the training purpose and the remaining 6 images are utilized for testing purpose. The Figure 6 shows some of the sample brain MRI images with tumor images.

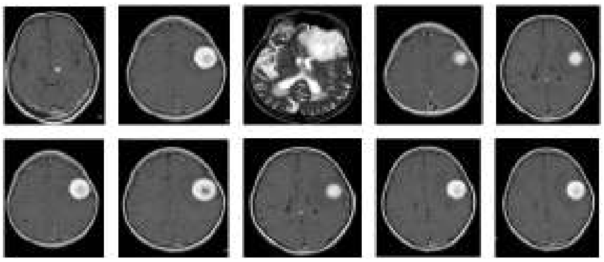
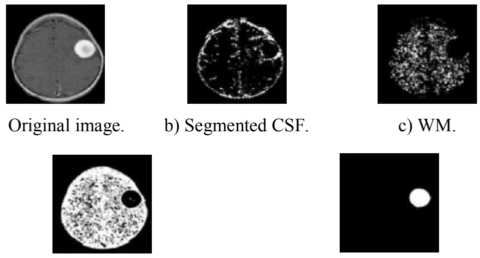


Figure 6. MRI image dataset.

4.2. Experimental Results

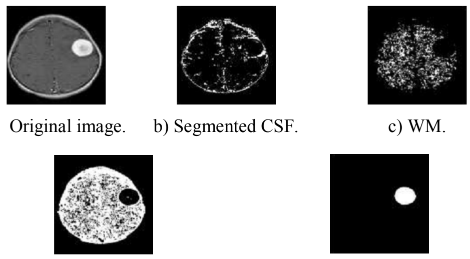
We have presented a technique for segmentation and detection of pathological tissues (Tumor), normal tissues (WM and GM) and fluid (CSF) from MR images of brain with the help of composite feature vectors comprising of wavelet and statistical parameters. The proposed technique can successfully segment the tumors as well as the brain tissues, provided that the parameters are set properly. The proposed technique is designed for supporting the tumor detection in brain images with tumor and without tumor. The obtained experimental results from the proposed technique are given in Figure 3, 4 and 5. The sample experimental results depicted in Figure 7, 8 and 9 shows the original image along with the segmented tissues such as CSF, WM, GM and the tumor region.



a) Original image. b) Segmented CSF. c) WM.

d) GM. e) Tumor region.

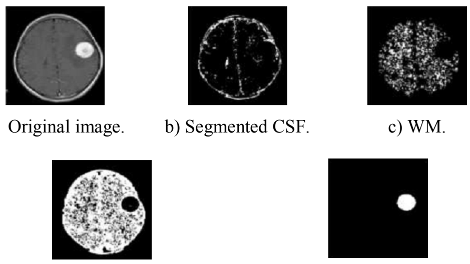
Figure 7. Experimental results of image 1.



a) Original image. b) Segmented CSF. c) WM.

d) GM. e) Tumor region.

Figure 8. Experimental results of image 2.



a) Original image. b) Segmented CSF. c) WM.

d) GM. e) Tumor region.

Figure 9. Experimental results of image 3.

4.3. Evaluation Metrics

The segmentation result is evaluated with the help of QR [10, 37] given as follows:

$$Quality\ rate, q_r = area(A \cap B) \ / \ area(A \cup B)$$

The evaluation of brain tumor detection in different images is carried out using the following metrics [40]:

$$Sensitivity = TP \ / \ (TP + FN) \tag{14}$$

$$Specificity = TN \ / \ (TN + FP) \tag{15}$$

$$Accuracy = (TN + TP) \ / \ (TN + TP + FN + FP) \tag{16}$$

Where, True Positive (TP), True Negative (TN), False Negative (FN) and False Positive (FP). Table 1 defining the relevant terms of the evaluation metrics like *TP*, *FP*, *FN*, *TN*.

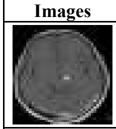
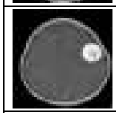
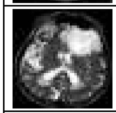
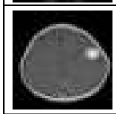
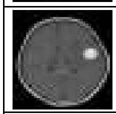
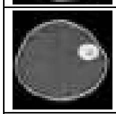
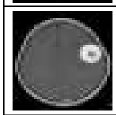
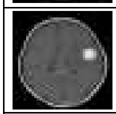
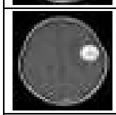
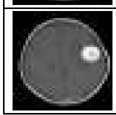
Table 1. Table defining the terms *TP*, *FP*, *FN*, *TN*.

Experimental Outcome	Condition as Determined by the Standard of Truth		Row Total
	Positive	Negative	
Positive	TP	FP	TP+FP
Negative	FN	TN	FN + TN
Column Total	TP+FN	FP+TN	N = TP+TN+FP+FN

4.4. Performance Evaluation of the Brain Tissue and Tumor Segmentation

Here, this section depicts the performance analysis of our proposed techniques with the relevant segmented results by means of the QR. The Table 2 portrays the QR of the brain tumor image with the corresponding segmented tissues such as CSF, WM, GM and the tumor region.

Table 2. Quality rate of the segmented brain tissues.

Images	Quality Rate			
	CSF	WM	GM	Tumor Region
	0.68961405	0.9871	0.909301268	0
	0.610229575	0.945	0.962626471	0.9987
	0.69624347	0.9987	0.942108948	0.9821
	0.809706458	0.9911	0.960468884	0.998
	0.665306415	0.963	0.949324752	0.992
	0.741233602	0.978	0.974303897	0.9823
	0.675816562	0.9954	0.992351728	0.99
	0.735918596	0.9789	0.9921	0.9865
	0.672507833	0.986	0.99	0.97
	0.677730931	0.99343	0.97	0.98765

4.5. Performance Evaluation of the Proposed Technique in Tumor Detection

The performance of our proposed brain tumor classification technique is evaluated by means of the standard existing classification techniques like K-NN classification and the Bayesian classification with the aid of the evaluation metrics values. The obtained values of the evaluation metrics of the NN is compared against the standard K-NN classification and the Bayesian classification. Here, with the aid of the input MRI image training and testing dataset, the values of TP, FP, FN, TN, Sensitivity, specificity and accuracy are given in Table 3. By analyzing the results, our proposed NN based tumor classification technique algorithm performs better than the existing ones. The results shows that the accuracy is proved with almost 80% of NN based classification and the Bayesian classification with detection of tumors from the brain MRI images.

Table 3. Detection accuracy of the proposed technique in training and testing dataset.

Input MRI image dataset			
Evaluation measures	K-NN classification	Neural Network	Bayesian classification
True Negative	3	3	2
False Positive	2	1	1
True Positive	1	2	2
False Negative	0	0	1
Specificity	0.6	0.75	0.67
Sensitivity	1	1	0.67
Accuracy	0.67	0.83	0.67

4.6. Comparative Analysis

We have compared our proposed brain tumor segmentation technique based NN is compared with the existing K-NN classification and the Bayesian classification with the aid of the evaluation metrics values such as Sensitivity, Specificity and the Accuracy. The classification techniques we have utilized for comparative analysis are K-NN classification and the Bayesian classification with the FFNN. The performance analysis has been made by plotting the graphs of evaluation metrics such as sensitivity, specificity and the accuracy. By analyzing the plotted graph, the performance of the proposed technique has significantly improved the tumor detection compared with the K-NN classification and the Bayesian classification. The evaluation graphs of the sensitivity, specificity and the accuracy graph is shown in Figure 10.

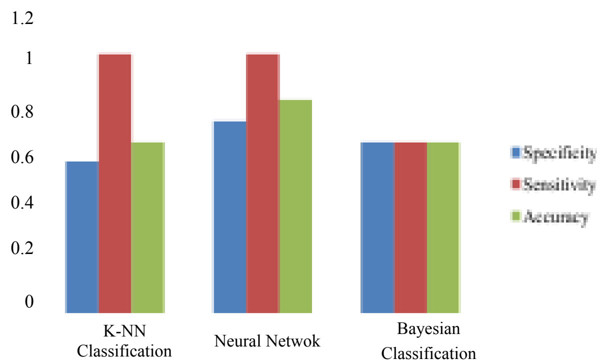


Figure 10. Comparative analysis graph.

5. Conclusions

In this paper, we have presented an effective NN based brain tumor detection technique with MRI images. The efficiency is achieved with brain tissue and tumor segmentation, feature extraction of the segmented regions and the classification based on NNs. The MRI image dataset contains 20 brain MRI images in which 10 images with tumor and the other 10 brain images without tumor is taken from the publicly available sources. The performance of the proposed technique is evaluated by means of the QR for all the segmented tissues. As well, the results for the tumor detection are validated through evaluation metrics namely, sensitivity, specificity and accuracy. The Comparative analysis is carried out K-NN classification and the Bayesian classification. The obtained results depicts that the proposed NN classification produces better results than the other classifiers in terms of sensitivity, specificity and accuracy.

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