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An Intelligent-Model for Automatic Brain-Tumor Diagnosis based-on MRI Images

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ABSTRACT
A brain tumor is the growth of abnormal cells within the brain; and it can be benign or malignant. Traditional diagnostic techniques involve invasive techniques such as biopsy, lumbar puncture and spinal tap method, to detect and classify brain tumors. A computer aided diagnosis algorithm has been designed so as to increase the accuracy of brain tumor detection and classification, and thereby replace conventional invasive and time consuming techniques. One of the most effective and common tool for diagnostic and treatment evaluation for brain interpretation has been magnetic resonance imaging (MRI). In this study an Intelligent-Model for Automatic Brain-Tumor Diagnosis Based-on MRI Images was introduced; in which, the (MR) images are classified into normal, Edema, Cancer, or Not classified. The proposed method consists of three stages: In the first stage a preprocessing of brain image is done to remove the noise and to increase and enhance the contrast using multiple steps, secondly texture features was extracted, and then reduced dimensionality based on PCA, and finally Back-Propagation Neural Network (BPNN) based-on Pearson correlation coefficient was used to classify the brain images. Experimental results show that our proposed model achieves accuracy of 96.8%

Keywords: Intelligent Model, Classification, Brain Tumor, Pearson correlation coefficient, BPNN.

1. INTRODUCTION
A brain tumor is the growth of abnormal cells within the brain, brain tumors can be benign or malignant, and it has a wide variety of symptoms. Brain tumors are the second leading cause of cancer-related deaths in children, and male, and fifth leading cause of cancer-related deaths in female in USA [1]. Till now; there are no known environmental-factors that cause or associated with brain tumors. Traditional diagnostic techniques involve invasive techniques such as biopsy, lumbar puncture and spinal tap method, to detect and classify brain tumors.

Medical imaging is often perceived to designate the set of techniques that noninvasively produce images of the internal aspect of the body. In this restricted sense, medical imaging can be seen as the solution of mathematical inverse problems; accordingly many imaging techniques can be performed for the early detection of brain tumors such as Computed Tomography (CT), Positron Emission Tomography (PET), but MRI has been the most effective and common tool for diagnostic and treatment evaluation, for brain interpretation.

Although MRI seems to be efficient in supplying the location and size of tumors, it is unable to classify tumor types [2], and the conventional method for brain-tumor detection and classification on MR images; is human inspection. Operator-assisted classification methods always are impractical for large amounts of data and are also non-reproducible.

2. LITERATURE REVIEW
Recently several computer-aided-diagnosis algorithms have been developed to improve the diagnostic performance of (MRI) in brain tumors classification, most notably, knowledge based techniques [3]. Chun-Ming Gu and Hui Ji who proposed a detection approach to distinguish the MR brain images as normal or abnormal the method uses DWT for extracting features, and PCA to reduce the number of features, and finally Adaptive back propagation neural network was chosen as a classifier.

In medical image analysis, the determination of tissue type (normal or pathological) and classification of tissue pathology are performed by using texture. MR image texture proved to be useful to determine the tumor type [4].Whereas, in 2012, Pauline John [5], presented his work on wavelet decomposition, textural feature extraction, and probabilistic neural network for further classification and tumor detection.

From the literature survey, firstly, it can be concluded that, various research works have been performed in classifying MR brain images into normal and abnormal [6], [7]. Whereas, more classification of MR brain images is highly needed, that is considered in this proposed method. Also, it is found that existing methods of brain tumor diagnosis and classification involve invasive techniques such as biopsy and spinal tap method [8]. It is essential to prevent and replace the invasive methods of brain tumor classification using a non-invasive method of brain tumor diagnosis, which has been focused our proposed technique.

The main objective of this study was to propose and develop of an intelligent-model to automate detection and classification of brain-tumor based on MRI images.

3. THE PROPOSED METHOD
Figure 1 shows the systematic overview of the proposed intelligent model for automated brain-tumor detection and classification. In the first step image is acquired from the MRI datasets which is then enhanced in preprocessing stage. In feature extraction stage, Principle Components Analysis is applied to get and dimensionally reduce the features of the image. In the classification stage, an adaptive dynamic Back-Propagation Neural Network (BPNN) based-on Pearson correlation coefficient was used to classify the brain images.

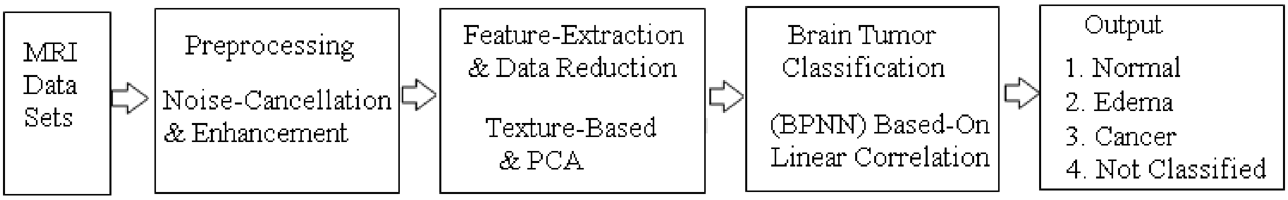


Figure (1): systematic overview of the proposed method

3.1 Preprocessing

In this stage MR image will be acquired and converted into data-form suitable for MATLAB environment, such as basic arithmetic operations, MATLAB stores an intensity image as a single matrix, each element of the matrix corresponding to one pixel. The matrix can be of class double, uint8, or uint16 [9]. Then preprocessing is done to convert Image to binary according to threshold, reduce the noise by filtration, and to enhance the MRI image through adjustment and edge detection as shown in figure (2) bellow.

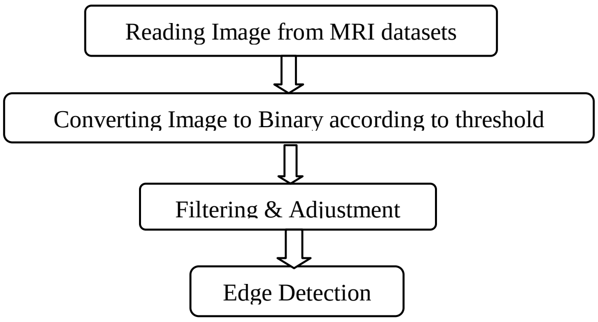


Figure (2): the proposed preprocessing algorithm

3.2 Feature Extraction and data manipulation

Detection based-on texture analysis makes differentiation of normal and abnormal tissue easy. It even provides contrast between malignant and normal tissue, which may be below the threshold of human perception. Texture analysis using computer aided diagnosis can be used to replace biopsy techniques and plays an important role in early diagnosis and tracking of diseases. In the proposed model a texture-based features was extracted.

Usually an image of size p × q pixels is represented by a vector in (p.q) dimensional space. In practice, however, these (p.q) -dimensional spaces are too large to allow robust and fast object recognition. A common way to attempt to resolve this problem is to use dimension reduction techniques. In order to reduce the feature vector dimension and increase the discriminative power. The principal component analysis (PCA) has been used to reduce the preprocessed MRI image from [64-by-64] into [64 -by- 1]. The implemented PCA algorithm can be described as follow:

Step 1: Get some data the image got 2dimensions matrix, binary image with edge values.

Step 2: Subtract the mean for PCA to work properly; you have to subtract the mean from each of the data dimensions. This produces a data set whose mean is zero.

Step 3: Calculate the covariance matrix Recall that covariance is always measured between 2 dimensions.

Step 4: Calculate the eigenvectors and Eigen values of the covariance Step 5: Choosing components and forming a feature vector here is where the notion of data compression and reduced dimensionality to form a feature vector [10].

3.3 Detection and Classification

To classify input-image feature vectors into target vectors, we used Artificial Neural Network (ANN), the proposed architecture is back-propagation feed forward; it provides a general solution to pattern classification problems by following Levenberg–Marquardt and Gradient-descent approaches for learning and training. The proposed architecture was consist of three layers; one hidden layer with ten neurons and input, output layers with sixty four neurons for each, as shown in Figure (3)

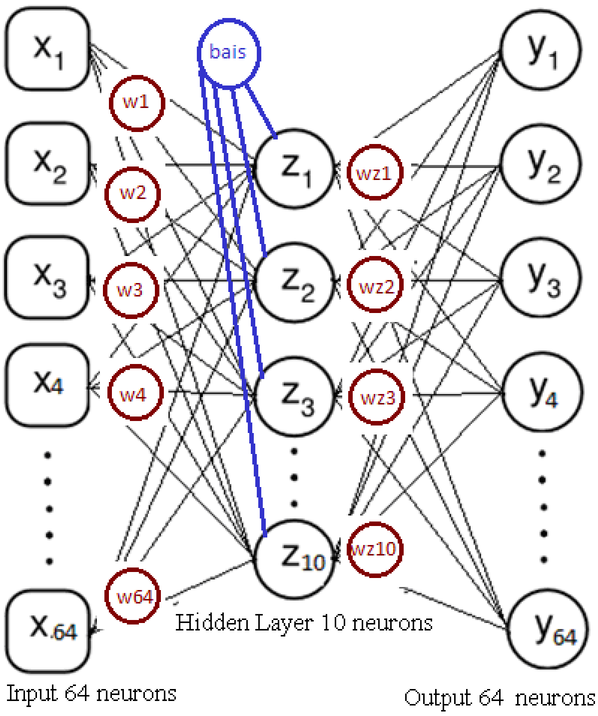


Figure (3): Theoretical architecture of Back-propagation Feed forward Network

3.3.1 *Learning and training*

Gradient descent with momentum weight and bias learning function was used for implementing the proposed network [11], and the resulted weight and biases was saved for each input image-vector, so as to avoid changing again with the new vector, and to overcome the huge number of networks for each input, as a result a dynamic neural network which change its initial values according to the input was configured. In addition Levenberg–Marquardt algorithm was used in training phase. In order to implement the Levenberg–Marquardt algorithm for neural network training, two problems have to be solved: how does one calculate the Jacobian matrix, and how does one organize the training process iteratively for weight updating [12]. The Levenberg–Marquardt algorithm:

$$\left(J^{T}J + \lambda\, daig(J^{T}J)\right)\delta = J^{T}[y - f(\beta)] \qquad (1)$$

Where

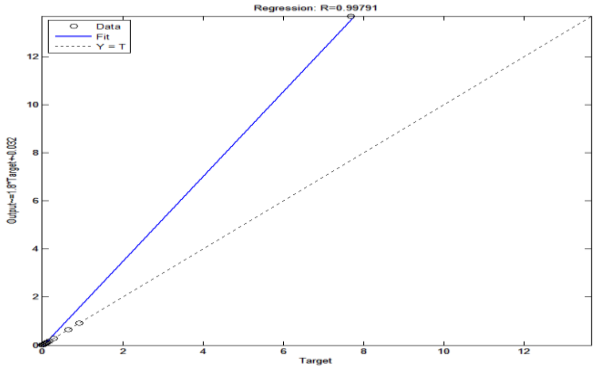
J = Jacobin matrix

λ = damping value

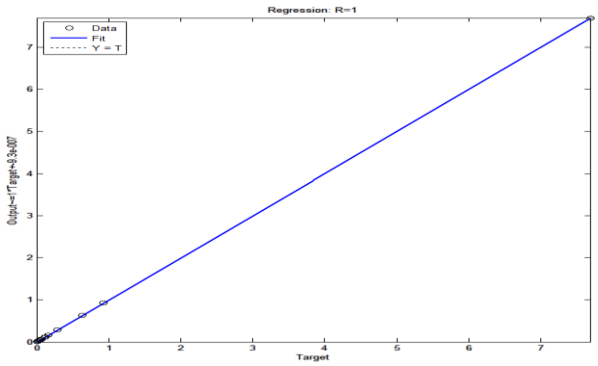
$f(\beta)$= activation function

δ = new value which added to the input weight

y = output value

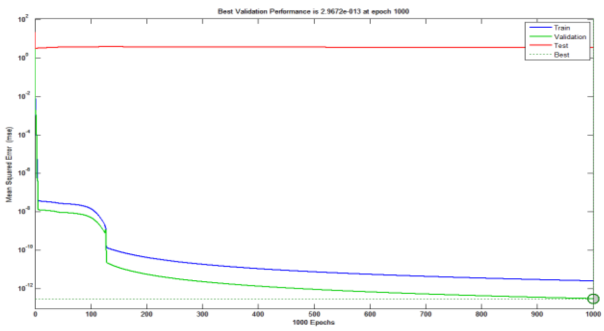


(a)

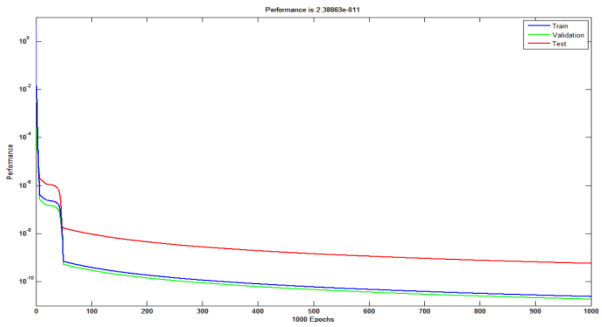


(b)

Figure (4): (a) Overall regression during first training, (b) Overall regression during 3rd training

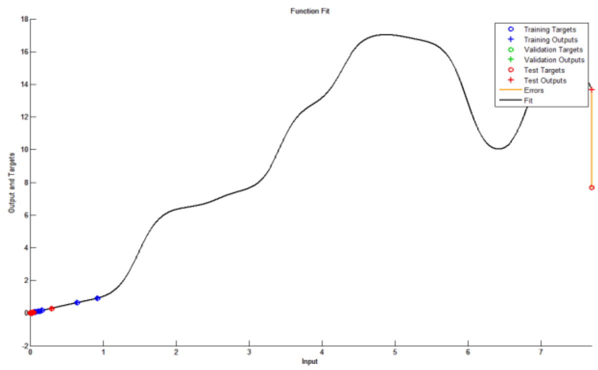


(a)

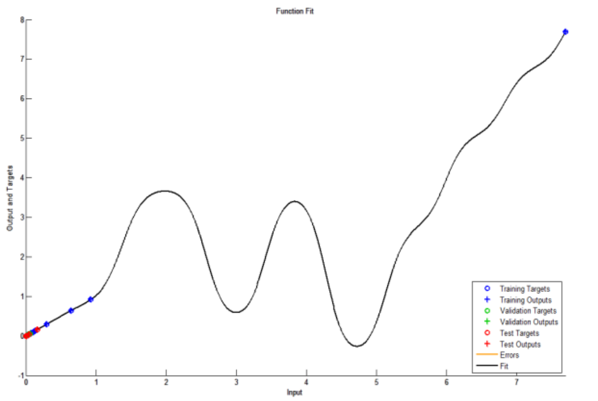


(b)

Figure (5): (a) Network performance during first training, (b) Network performance during 3rd training



(a)



(b)

Figure (6): (a) network fitting line during first training (b) network fitting line during 3rd training

3.3.2 Decision making

In this sub-phase, Pearson product moment correlation coefficient has been used to measure the linear correlation between the output-image-vector matrix and the saved target-image-vector. The mathematical formula for Linear Correlation Coefficient (r) computing r is:

$$r = \frac{n\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{n(\Sigma x^{2}) - (\Sigma x)^{2}}\sqrt{n(\Sigma y^{2}) - (\Sigma y)^{2}}} \qquad (2)$$

Where (n) is the number of pairs of data.

Classification and Detection accomplish by observing several parameters resulted from network training such as: performance, fitting, mean squared error or linear regression between the output and the target which is made before as reference data. Accordingly the output phase involves the application of the intelligent-model to observe how well it reacts to the untrained data. User is required to enter the MRI-image file name, then after several stages, correlation coefficient (r) is calculated and compared with the saved the correlation coefficients, which was made in training phase. Noted that, the target-saved MRI-Image vectors, was categorized according to the trained-correlation-coefficients, into four classes Normal, Edema, Cancer, and Not-classified.

4. EXPERIMENTAL RESULTS

Brain cancer is most treatable and curable if caught in the earliest stages of the disease. Untreated or advanced brain cancer can only spread inward because the skull will not let the brain tumor expand outward. This puts excessive pressure on the brain, causing increased intracranial pressure and can cause permanent brain damage and eventually death [5].

The proposed model is implemented on a three MRI-human brain datasets each consist of 58 images, once our data set is collected, and a single image file was selected; we follow different steps of our system described in the previous Sections. After program execution the result will be as shown in figures (7), and (8) bellow.

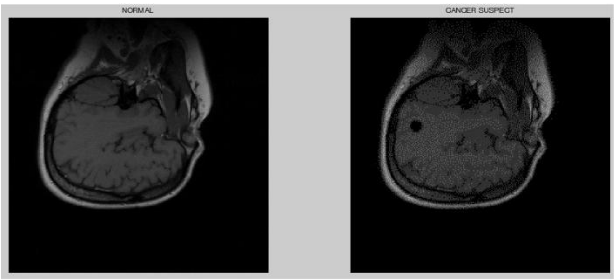


Figure (7): normal and abnormal image for class3 (Cancer)

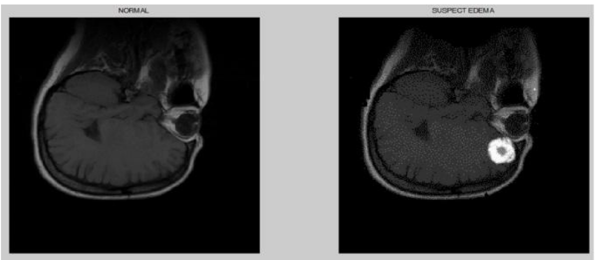


Figure (8): normal and abnormal image for class2 (Edema)

4.1 Performance Evaluation:

In this section, we present the performance evaluation methods used to evaluate the proposed approaches. We assess the performance of the proposed method in terms of sensitivity, specificity and accuracy. The three terms

$$\text{Sensitivity}=TP/(TP+FN)100\% \quad (3)$$

$$\text{Specificity} = TN/(TN+FN)\ 100\% \quad (4)$$

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN)100\% \quad (5)$$

Where:

TP (True Positives) = correctly classified positive cases.

TN (True Negative) = correctly classified negative cases.

FP (False Positives) = incorrectly classified negative cases.

FN (False Negative) = incorrectly classified positive cases.

5. CONCLUSIONS

Brain-tumor classification using brain MRI is a main problem for doctors and practitioners to get valuable results. Previously proposed systems have certain problems that require crucial investigation; system performance can be improved by getting higher detection rate and reducing misclassification. The proposed model in this study is proficient for classification to classify the MRI-Brain-tumor into normal, Edema, Cancer, or Not-classified, the model was designed using advanced preprocessing techniques, feature-extraction, PCA, and adaptive back propagation neural network. The experimental results have shown that the proposed system achieves validity as competitive results quality-wise, and showed a performance with the accuracy rate of above 96.0%,

6. REFERENCES

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