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BRAIN TUMOR CLASSIFICATION USING NEURAL NETWORK BASED METHODS

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ABSTRACT
MRI (Magnetic resonance Imaging) brain neoplasm pictures Classification may be a troublesome tasks due to the variance and complexity of tumors. This paper presents two Neural Network techniques for the classification of the magnetic resonance human brain images. The proposed Neural Network technique consists of 3 stages, namely, feature extraction, dimensionality reduction, and classification. In the first stage, we have obtained the options connected with tomography pictures victimization distinct moving ridge transformation (DWT). In the second stage, the features of magnetic resonance pictures (MRI) are reduced victimization principles part analysis (PCA) to the more essential options. In the classification stage, two classifiers primarily based on supervised machine learning have been developed. The first classifier supported feed forward artificial neural network (FF-ANN) and therefore the second classifier supporter Back-Propagation Neural Network. The classifiers have been wont to classify subjects as normal or abnormal tomography brain pictures. MRI (Magnetic resonance Imaging) brain neoplasm pictures Classification may be a troublesome task thanks to the variance and complexity of tumors. This paper presents two Neural Network techniques for the classification of the magnetic resonance human brain images. The proposed Neural Network technique consists of 3 stages, namely, feature extraction, dimensionality reduction, and classification. In the first stage, we have obtained the options connected with tomography pictures victimization distinct moving ridge transformation (DWT). In the second stage, the features of magnetic resonance pictures (MRI) are reduced victimization principles part analysis (PCA) to the more essential options. In the classification stage, two classifiers primarily based on supervised machine learning have been developed. The first classifier supported feed forward artificial neural network (FF-ANN) and therefore the second classifier supported Back-Propagation Neural Network. The classifiers have been wont to classify subjects as normal or abnormal tomography brain pictures**.**

KEYWORDS: MRI; Feature Extraction; Feature Selection; Tumor Classification; Feed forward Neural Network; Back-Propagation Neural Network.

INTRODUCTION
Early detection and classification of brain tumors is very vital in clinical observe. Many researchers have proposed totally different techniques for the classification of brain tumors based on totally different sources of information. In this paper we propose a method for brain tumor classification, focusing on the analysis of Magnetic Resonance (MR) images and Magnetic Resonance Spectroscopy (MRS) knowledge collected for patients with benign and malignant tumors. Our aim is to achieve a high accuracy in discriminating the 2 types of tumors through a mix of many techniques for image segmentation, feature extraction and classification. The proposed technique has the potential of assisting clinical identification. Necessary preprocessing steps prior to characterization and analysis of regions of interest (ROIs) are segmentation and registration. Image registration is used to see whether 2 subjects have ROIs in the same location. However, in this work we do not take into consideration the placement of the growth in the classification model so we tend to do not use registration. Image segmentation is required to delineate the boundaries of the ROIs ensuring, in our case, that tumors are printed and labeled systematically across subjects. Segmentation can be performed manually, automatically, or semi-automatically.
The manual method is time intense and its accuracy extremely depends on the domain knowledge of the operator. Specifically, various approaches have been projected to deal with the task of segmenting brain tumors in MR

images. The performance of these approaches usually depends on the accuracy of the spatial probabilistic information collected by domain specialists. In previous work, we projected associate degree automatic segmentation rule that is supported the fuzzy connectedness concept. The main idea is to assign to each combine of voxels, x, y, in the image, a real number between zero and one indicating their connectedness. Starting with many seed points, all the voxels are mechanically appointed to the structure to which they have the very best connectedness price. Utilizing the statistical info cumulated throughout the segmentation process, this method will offer satisfying results even in cases where the boundaries of the ROIs cannot be easily known.

Having segmented the ROI and in order to make a classification model, one needs to extract a collection of discriminative features from the ROI. Most characterization techniques are primarily based on extracted global visual options that refer to the complete image rather than to regions that are of interest. However, in medical images, feature extraction has to specialize in specific regions and capture not only form however additionally structural and internal volume properties that can be helpful for building a classification model. Megalooikonomou et al. proposed a methodology that expeditiously extracts a kdimensional feature vector using homocentric spheres in 3D (or circles in 2D) radiating out of the ROI's center of mass. The method has been applied with success to classification and similarity searches of spatial ROIs. In this paper, we propose associate approach (see Figure 1) for building a classification from the MR pictures, and a group of options is extracted. Instead of employing all of the features to build the model, a preprocessing step of feature selection is model performed aiming to remove the redundant options. Based on the applied mathematics information, only the most for informative options extracted from the MR pictures area unit utilized in the model building process. In addition, in this paper,
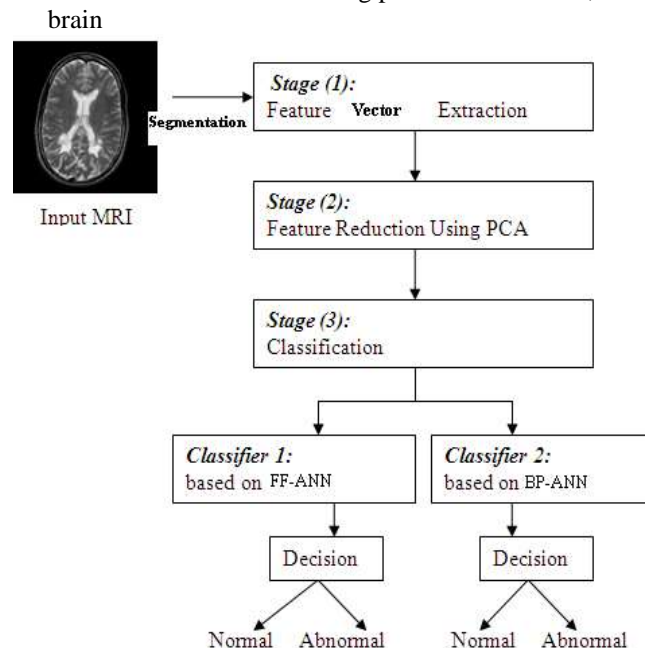
Figure 1. Proposed Work Model

We consider features from other sources (e.g., MRS data) in the classifier training process. This leads to improved classification accuracy.

Methodology
There are four major steps in the projected approach for brain tumor classification: (a) ROI segmentation: delineating the boundary of the tumor (ROI) in associate man image; (b) feature extraction: getting substantive features of the ROI known in the previous step; (c) feature selection: removing the redundant features; (d) classification: learning a classification model using the features.

    A. Segmentation
Within the segmentation method, each image region confined by a rectangular window is represented by a feature vector of length R. These vectors computed for Q hand-picked regions area unit organized in the pattern matrix

PR,Q and kind clusters in the R-dimensional area. The Q pattern vectors in P area unit fed into the input NN layer, while the range C of the output layer components represents the desired number of segmentation categories. In each epoch of the network coaching method, the network weights WC,R are recalculated by minimizing the distances between each input pattern vector and the corresponding weights of the winning neuron characterized by its coefficients nearest to the current pattern. In case that the method is successfully completed, the network weights belonging to separate output elements represent typical category people. In this paper, the region segmentation process includes of coaching the NN on all image regions extracted by an oblong window with 0.5 overlap, and subsequent exploitation of the trained network for region classification. The algorithm includes of the following ordered 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 [10] 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.

B. *Feature Extraction*

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

$$(1)\ W\psi(a,b) \equiv \int_{\neg\infty}^{\infty} f\ (x) \bullet \psi a,\ \ b(t)\partial x$$

$$\text{Where } \psi a,\ \ b(t) \equiv \frac{1}{\sqrt{|a|}}$$

And the wavelet Ψa, b is computed from the mother Ψ wavelet by translation and dilation, wavelet, the dilation factor and b the translation parameter (both being real positive numbers). Under some mild assumptions, the mother wavelet Ψ satisfies the constraint of having zero mean. The eq. (1) can be discretized by restraining a and b to a discrete lattice (a = 2b; a € R+; b € R) to give the discrete wavelet transform (DWT). The discrete wavelet transform (DWT) is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale. DWT can be expressed as.

$$(2)\ DWT_{x(n)} \equiv \begin{cases} dj,k = \sum(x(n)h*j(n-2jk)) \\ dj,k \equiv \sum(x(n)g*j(n-2)jk)) \end{cases}$$
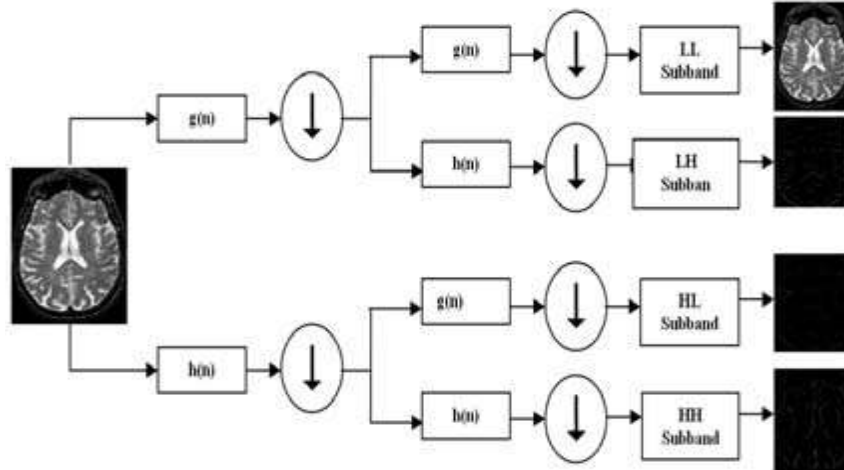
The coefficients dj, k, refer to Figure2: DWT Schematically

The detail components in signal x(n) and correspond to the wavelet function, whereas aj,k, refer to the approximation components in the signal. The functions h(n) and g(n) in the equation represent the coefficients of the high-pass and low-pass filters, respectively, whilst parameters j and k refer to wavelet scale and translation factors. The main feature of DWT is multiscale representation of function. By using the wavelets, given function can be analyzed at various levels of resolution. Fig. 2 illustrates DWT schematically. The original image is process along the x and y direction by h(n) and g(n) filters which, is the row representation of the original image. As a result of this transform there are 4 subband (LL, LH, HH, HL) images at each scale. (Fig.2). Subband image LL is used only for DWT calculation at the next scale. To compute the wavelet features in the _rst stage, the wavelet coefficients are calculated for the LL subband using Harr wavelet function.

C.   Feature Selection and Reduction

One of the foremost common varieties of dimensionality reduction is principal parts analysis. Given a set of information, PCA finds the linear lower-dimensional representation of the knowledge specified the variance of the reconstructed knowledge is preserved. Using a system of feature reduction supported a combined principle element associate degree aliases on the feature vectors that calculated from the wavelets limiting the feature vectors to the element elite by the PCA ought to cause an economical classification algorithmic rule utilizing supervised approach. So, the main idea behind victimization PCA in our approach is to cut back the spatiality of the moving ridge coefficients. This leads to more economical and correct classifier.

The feature extraction process was carried out through 2 steps: foremost the rippling coefficients were extracted by the DWT and so the essential coefficients are selected by the PCA.
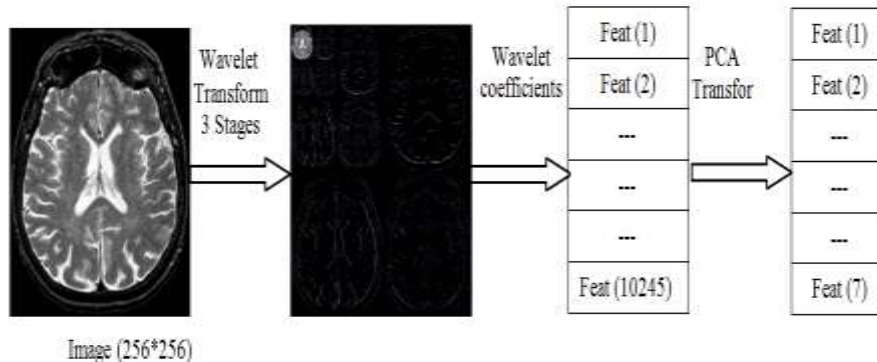

Figure3: Schematic diagram for the used feature Extraction and reduction scheme

Model Learning

A. Feed Forward Artificial Neural Network (FFANN) Based Classifier

A three layer neural network was created with five hundred nodes within the 1st (input) layer, 1 to fifty nodes in the hidden layer, and 1 node as the output layer. We varied the variety of nodes within the hidden layer in a very simulation so as to work out the best variety of hidden nodes. This was to avoid over fitting or under fitting the information. Due to hardware limitations, ten nodes in the hidden layer were selected to run the final simulation. Figure 2 shows the style of the Feed Forward Neural networks utilized in this analysis.

The 500 knowledge points extracted from every subject were then used as inputs of the neural networks. The output node resulted in either a 0 or one, for control or patient knowledge severally. Since the nodes in the input layer could soak up values from an outsized vary, a transfer function was used to remodel knowledge 1st, before sending it to the hidden layer, and then was transformed with another transfer operate before causing it to the output layer. In this case, a tan sigmoid transfer function was used between the input and hidden layer, and a log sigmoid function was used between the hidden layer and the output layer.
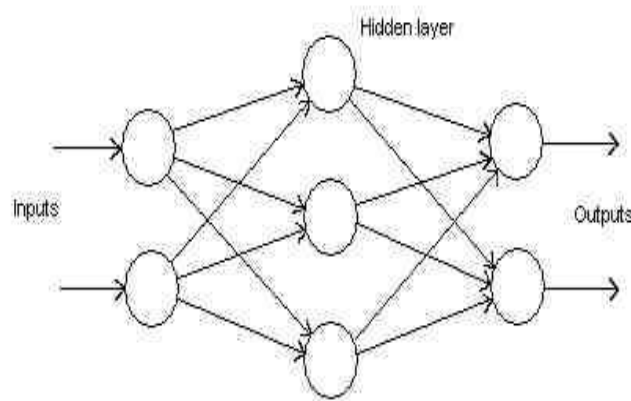

Figure 4: Feed Forward Neural Network

The weights in the hidden node needed to be set victimization "training" information. Therefore, subjects were divided into training and testing datasets. Out of the 69 subjects, a pair of random patients and 2 random controls were chosen as "test data", while the rest of the dataset was used for coaching. Training information was used to feed into the neural networks as inputs and then knowing the output, the weights of the hidden nodes were calculated using back propagation algorithm. 120 trials were performed on the same Neural Network, selecting sixty five subjects indiscriminately every time for preparation and four remaining subjects for testing to search out accuracy of Neural network prediction.

B. Back Propagation Artificial Neural Network (BP-ANN) Based Classifier

The most widely used neural-network learning technique is that the BP algorithmic rule. Learning in a neural network involves modifying the weights and biases of the network in order to reduce a price function. The cost function invariably includes Associate in Nursing error term alive of however shut the network's predictions area unit to the category labels for the examples within the coaching set. Additionally, it may embody a complexness term that reacts a previous distribution over the values that the parameters will take.

The activation function considered for each node in the network is the binary sigmoidal function defined (with s = 1) as output = $1/(1+e-x)$, where x is the sum of the weighted inputs to that particular node. This is a common function used in many BPN. This function limits the output of all nodes in the network to be between 0 and 1. Note all neural networks are basically trained until the error for each training iteration stopped decreasing.
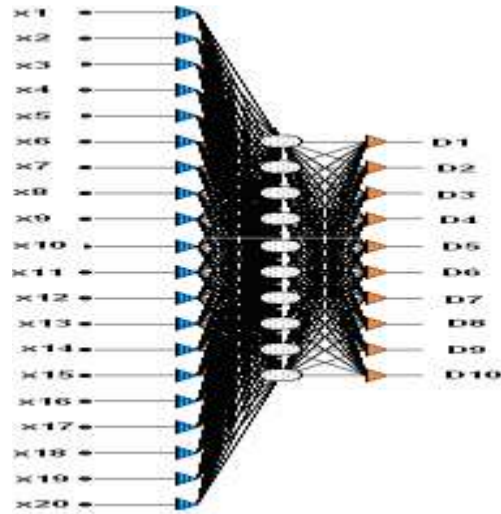
Figure 5: Back Propagation Neural Network

Figure 5 shows the design of the specialized network for the prediction of stroke unwellness. The complete set of ultimate data (20 inputs) is given to the generic network, in which the ultimate designation corresponds to output units. The net inputs and outputs of the j hidden layer neurons may be calculated as follows

$$net_j^h = \sum_{i=1}^{N+1} W_{jiX_i}$$

$$y_j = f\,(net_j^h)$$

Calculate the net inputs and outputs of the k output layer neurons are

$$net_k^o = \sum_{J=1}^{J+1} V_{jk}\,y_j$$

$$Z_k = f\,(net_k^o)$$

Update the weights in the output layer (for all k, j pairs)

$$V_{kj} \leftarrow V_{kj} + C\lambda(d_k - Z_k)Z_k\,(1 - Z_k)\,y_j$$

Update the weights in the hidden layer (for all i, j pairs)

$$W_{ij} \leftarrow W_{ij} + C\lambda^2 y_j\,(1 - y_j)x_i\,(\sum_{k=1}^{k}(d_k - z_k)z_k\,(1 - z_k)v_{ik})$$

 Update the error term

$$E \leftarrow E + \sum_{k=1}^{k}(d_k - z_k)^2$$

and repeat from Step 1 until all input patterns have been presented (one epoch). If E is below some predefined tolerance level, then stop. Otherwise, reset E = 0, and repeat from Step 1 for another epoch.

CONCLUSION
In this paper, we propose 2 approaches for Brain growth Detection supported artificial neural networks. The networks were categorized into feed-forward neural networks and Back propagation neural Network. The purpose is to develop tools for discriminating malignant tumors from benign ones assisting deciding in clinical diagnosing. The proposed approach utilizes a combination of those 2 neural network techniques and consists of many steps as well as

segmentation, feature vector extraction and model learning. These two ways will then be used to filter non-suspecting brain scans likewise on imply suspicious regions that have similar property because the growth regions.

ACKNOWLEDGEMENTS

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