MRI-Based Brain Tumor Detection and Classification Using Artificial Neural Network

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Abstract. The process of brain tumor categorization and identification using MRI (magnetic resonance imaging) is one of the challenging domains in medical field. There were numerous malignancies such as glioma tumor, no tumor (benign), pituitary tumor and meningioma tumor.In this paper, an efficient automated methodhas been proposedto identify and classify tumor image from the MRI images.This proposed methodology includes three processing steps, including pre-processing, segmentation and feature classification from MRI images. In this,the Otsu thresholding technique is first applied to separate tumor from input brain image. Then then combination of three methods, namelyDWT(Discrete wavelet transform), PCA (Principal Component Analysis) and GLCM (Gray level co-occurrence matrix) to extract image attributes from the fragmented MRI data. Further, the extracted feature images are applied to the classifiers namely Naive Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Decision Tree (DT). Analysing the results of above machine learning classifiers, the Artificial Neural Network (ANN) model obtains a 97.6% accuracy rate and the minimum loss rate of 0.028817. It is evident from the experimental result, the proposed method has a great chance of detecting tumor efficiently.

Keywords: Brain Tumor Classification, Segmentation, Artificial Neural Network, Tumor detection.

1 Introduction

Brain tumor is caused by aberrant cell proliferation. The study's purpose is to reliably identify and classify brain tumors by employing a number of approaches in clinical image refining, model study, and machine vision for brain diagnostic magnification, fragmentation, and categorization. Numerous studies have been conducted to detect, fragment and categorize the affected portion in scanned images. Shermin Shamsudheenet.al have carried out the biologically Inspired Orthogonal Wavelet Transformation with Deep learning technique based Brain Tumor detection & Classification in 2D slice MRI images [1]. A.K.Aggarwal implemented and learned texture features based on GLCM for performing Brain TumorClassification in MRI Images [2].

IACIDS 2023, November 23-25, Lavasa, India

DOI 10.4108/eai.23-11-2023.2343221

Z Indra et.al [9] also extracted GLCM features anddifferentiatednormal brain and abnormal brain Images. The state of art techniques mainly focuses on classifying and detecting tumor images. If the position of an exact tumor region is not accurately identified then these techniques based brain tumor detection may be ineffective.The GLCM are an important feature descriptors that may be utilized to locate the region of interest in any brain image.Jaeyong Kang et.al proposed machine learning classifierswith ensemble of deep features algorithm for brain tumor classification[7].W Widhiarso et.al proposed a combined DWT with GLCM based feature extraction and machine learning classification algorithm[8]. MT El-Melegy et.al performed a comparative study of various automated classification algorithms for multimodal tumor segmentation [10]. NB Bahadure et.al proposed a generic algorithm based comparative approach for brain tumor segmentation and classifcation [11]. An automated technique based on classification and feature-based analysis may outperform existing state-of-the-art methodologies.

This paper is to deal with the automated brain tumor identification and brain tumor categorization. MRI scans are used to analyze brain images. It aims to detect if the given MRI scan has a tumor or not in the Stage 1 and if found it then classifies the tumor as glioma, malignant or pituitary. Database used for brain images and experimental setups are detailed in Section I. The methods have been described in section II. The research findings Training, evaluation and result analysis are explained in the section III and concluded this research article in section IV.

2 Database and Experimental Setup

This research work used SartajBhuvaji dataset, which contains four classes of tumors: glioma tumor, pituitary tumor, malignant tumorand no tumor and it is composed of 826 MRI images of glioma tumor, 247 images of malignant tumor type, 827 images of pituitary tumor type and 328 of no tumor category of MRI images.

2.1 Dataset

Table 1. SartajBhuvaji dataset

Types of Tumor	Training	Testing
Glioma Tumor	826	101
Malignant Tumor	247	128
Pitiutary Tumor	827	100
No Tumor	328	105

2.2 Experimental Setup

Processor: Any AMD x86-64 processor or Intelx86-64 processor with 8 GB of RAM

Disk Space: 8 GB

Software Requirements: MATLAB 2018b or later

Operating System: Windows 10

3 Methodology

The MRI images are given as input, Gaussian filters are applied for pre-processing to eliminate noise in the MRI images. An image segmentation process is employed to isolate the tumor and non-tumor area from these MRI images. Otsu’s thresholding method is used for segmenting the MRI image, Otsu is a non-linear method that turns a grayscale picture into a binary representation by assigning two levels to each pixel based on whether it is below or above the set threshold value. The features have been extracted through DWT, it was utilized for wavelet coefficients calculation from MRI Brain images. and PCA is utilized to high dimensionality reduction of data. These extracted features are finally classified using the various classifiers. The proposed methodology pipeline is illustrated in Figure1.

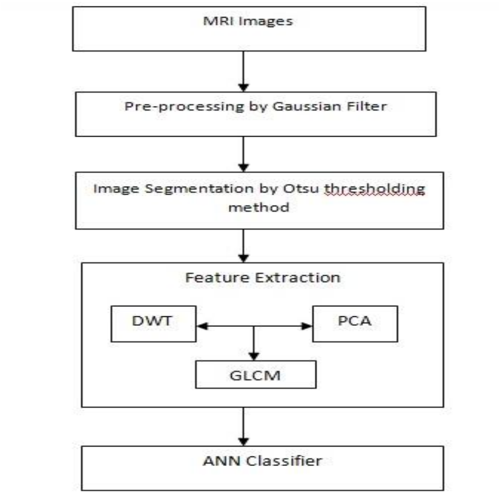


Fig 1. The proposed method pipeline

Pre-processing:

Preprocessing through a Gaussian filter involves applying a Gaussian blur to an image or a dataset. This approach is often used in image visualizing and machine vision jobs to minimize noise and smooth out the picture or data.

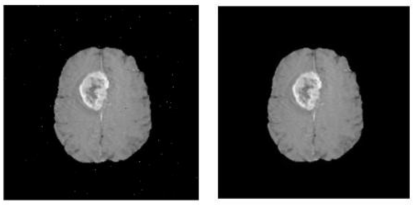


Fig 2. Preprocessing the MRI image with and without noise.

Segmentation:

Otsu's method automatically converts a grayscale image to a binary image using clustering-based thresholding. The algorithm assumes a bi-modal histogram and identifies the optimal threshold to separate foreground and background pixels to minimize the combined spread within the classes, or maximize the inter-class variation.

Feature Extraction:

The combination of DWT and PCA with GLCM are used to extract the features in this proposed method.A number of filtering and down sampling techniques are used in the DWT. It divides the incoming signal into two components: approximation and detail, using a pair of filters known as the analysis filters. The approximation component represents the signal's low-frequency components, whereas the detail component represents the signal's high-frequency components.

Let x[n] be the input signal of length N.

The DWT of x[n] is obtained by applying a series of convolutions and down sampling operations.

$$aj[k] = (h * x)[k] = \Sigma\, x[n] * h[n-2k] \quad (1)$$

Where aj[k] represents the jth level approximation coefficients, h[n] is the low-pass filter, * denotes convolution, and k represents the down sampled index.
Similarly, the detail coefficients bj[k] at the jth level are obtained by convolving the input signal with a high-pass filter g[n]:

$$bj[k] = (g * x)[k] = \sum x[n] * g[n - 2k] \quad (2)$$

Feature extraction and dimensionality reduction in medical image processing are commonly done using the PCA method. It assists for determining the most important patterns or components in a dataset.

GLCM:

GLCM assists in the extraction of second order statistical textural information from pre-processed images. The GLCM of an image is described as a frequency matrix at which two pixels in the picture are separated by a vector. The parameters like Energy , Contrast , Correlation , and Homogeneity)are calculated for each block in the preprocessed MRI scan images, and the final one is used to classify tumor regions.

$$\mathrm{Energy} = \sum_{\mathrm{mn}=0}^{\mathrm{N}-1} (\mathrm{CS}_{(\mathrm{mn})})^2 \quad (3)$$

$$Contrast = \sum_{mn=0}^{N-1} \mathrm{CS}_{(\mathrm{mn})}(m-n)^2 \quad (4)$$

$$Correlation = \sum_{\mathrm{mn}=0}^{\mathrm{N}-1} \mathrm{CS}_{\mathrm{mn}} \frac{(\mathrm{m}-\mu)(\mathrm{n}-\mu)}{\sigma^2} \quad (5)$$

$$Homogeneity = \sum_{mn=0}^{N-1} \frac{CS_{(mn)}}{1+(m-n)^2} \quad (6)$$

Where,

$CS_{(mn)}$ = Element m,n of the normalized symmetrical GLCM

N = Number of gray levels in the image as specified by Number of levels

μ = GLCM mean (being an estimate of the intesity of all pixels in the realtionships that contributed to the GLCM)

$\sigma^2 = The\ variance\ of\ the\ intensities$ of all reference pixels in the relationships that contributed to the GLCM

ARTIFICIAL NEURAL NETWORK (ANN) CLASSIFIER

To increase detection accuracy, feature fusion allows comprehensively characterizing segmented features and providing compact representations of included image features. To differentiate the segmented and non-segmented regions, DWT,PCA and GLCM features are fused and employed as a function vector for an ANN Classifier. In this work, ANN is used to identify segmented and non-segmented regions and a network architecture consisting of 13 input features and 10 hidden layers.

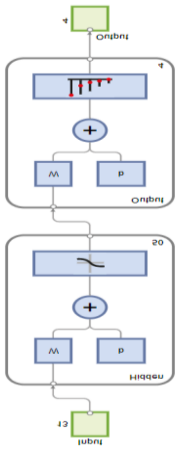


Fig 3. ANN Prototype

4 Results

This part elucidated the experimental findings of proposed method. Tumor MRI images of sartajbhuvaji dataset are experimented in this method. The proposed approach was created using MatLab 2018b, 8192 Megabyte of Memory, and dual kernel. The MRI scanned illustrations are pre-treated and extracted the attributes using discrete wavelet and PCA with GLCM. To create the input vector for the MLP NN classifier, these parameters are merged. The Artificial Neural Network (ANN) – Multi Layer Perceptron (MLP) Neural Network classifier is trained using these features. The MLP-based neural networks were trained over 1000 epochs with the Bayesian Regularization (BR) training function. With ten hidden layers, the best training time performance is 0.028817. Following the training, each sample's performance metric approaches the goal.

Table 2. Combination of features & Accuracy

Combination of Features	Overall Accuracy (%)
OTSU + (DWT + PCA) + SVM	56
OTSU + CNN	87
GLCM	82
Proposed Method (DWT+PCA+GLCM)	**97.6**

The GLCM feature values are extracted in order to identify the grey level similarity between pixels, and the resultant features are used to generate the final feature vectors. The resultant vectors are split into two categories, Thirty percent are utilized for testing, while seventy percent are for training. Table 2 demonstrates that the proposed feature combination provides an overall accuracy of 97.6%.

Table 3. Comparison of ANN with other Classifiers

	Naïve Bayes (%)	KNN (%)	SVM (%)	Decision Tree (%)	ANN (%)
DWT+PCA+GLCM	81	86	92	84	97.6
Cross Validation	80	87	90	85	94

The feature vectors are trained and tested using many classifiers, as Table 3 illustrates. ANN outperforms with the high accuracy of 97.6% when compared to other classifiers. The experiment was performed ten times to make sure that the proposed method was reliable and had a 94% cross validation accuracy.

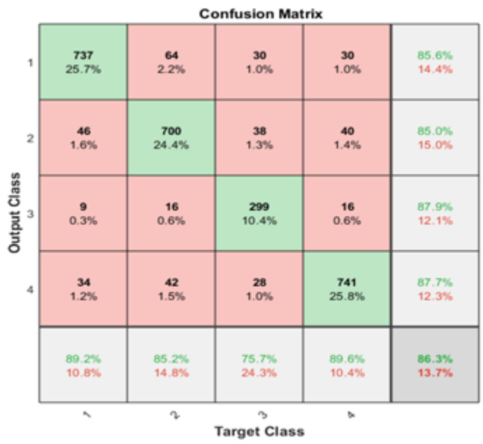
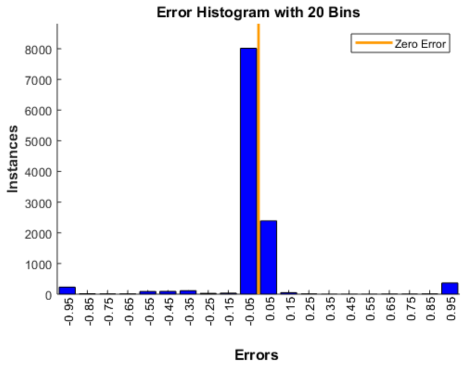


Fig.4. Confusion matrix for the training model

Confusion matrix is a compendious tabulation that is utilized to measure the categorization model's effectiveness.. The number of appropriate or inappropriate prognosticis summarized with the computed merits and sorted by groups. It is illustrating the effectiveness of the model.



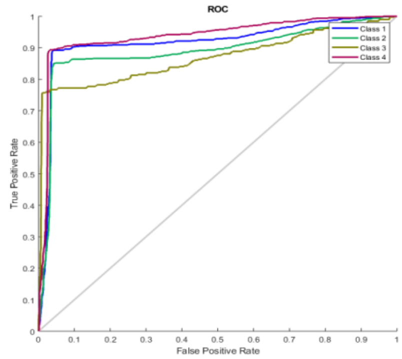
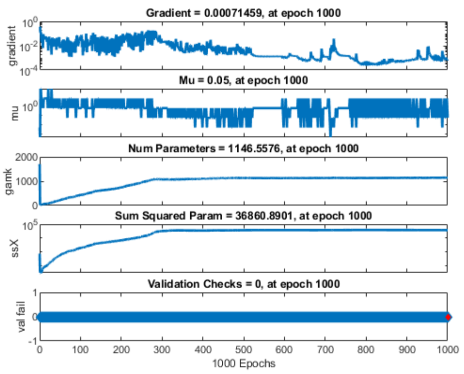


Fig.5a. Error histogram,

Fig.5b. ROC of ANN Classifier

The error histogram quantifies the error distributions as the outcomes on ANN predictions. In the act of it get away from the zeroth point, the probability of making a mistake will decrease. The results, as illustrated in figures 5a and 5b, demonstrate that ANN properly completes the prediction with acceptable error distributions.The MLP-NN Receiver Operating Characteristics curve (ROC curve)is utilized to ascertain the categorization efficacy of the ANN, as seen in this figure.



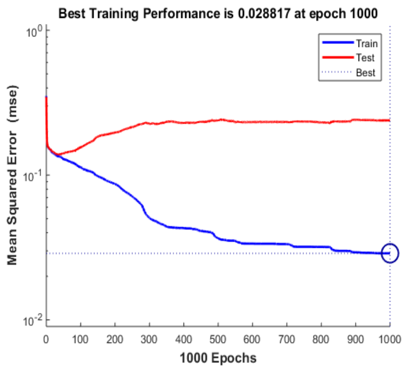


Fig.6a. Results of the training data

Fig.6b. Berst training performance result

5 Conclusion

In this study, the comparision of the brain tumor identification and categorization outcomes of various classifiers for brain tumor fragmentation.In the Brain-Tumor-Classification-(sartajbhuvaji) dataset, 70% MRI volumes are selected randomly for training the classifiers, with another arbitrary 30% chosen for testing.The efficient feature elicited fromthe ANNbased MLP algorithm is demonstrated the highest performance compared to other classifiers.This method achieved a higher classification accuracy of 97.6% and the less error of 0.028817 loss in comparision to the latest techniques. The future work focuses on widening the feature set utilized by the classifiers should encompass additional features to enhance tumor categorization.

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