Original Research Article

Deep Neural Network approach based Segmentation, Detection, and Classification of Brain Tumor

ABSTRACT

The segmentation, detection, and extraction of malignant tumor regions from magnetic resonance (MR) images is an important clinical task. Still, it is a time-consuming and complicated assignment for medical analysts. To eliminate such limitations, computer aid becomes essential. The deep Neural Network approach plays an impressive role in both time optimization and accuracy, allowing clinicians to distinguish malignant and benign patterns automatically. Herein, we propose an effective method for the segmentation, detection, and classifying of brain tumor MR images based on multilayer deep neural networks (MDNN). The proposed system comprises multiple stages. The Median filters are used in the pre-processing step, and morphological operation and Otsu thresholding are used to segment MR images. Discrete Wavelet Transform (DWT) algorithm is considered in the extraction features, and their classification is executed by a convolutional neural network (CNN) and support vector machine (SVM) algorithms. We use MATLAB simulation and experimental findings to evaluate the suggested method's performance on the brain's complex and highly 2D structures. The results show that the methodology is reliable and efficient, with 93.5 percent accuracy.

Key words: Image Processing, Brain Tumor Detection, Image Segmentation, MRI, SVM, Deep Learning, Multilayer Neural Network

1. INTRODUCTION

Diagnostic image segmentation in magnetic resonance imaging (MRI) [1] or any other medical imaging modalities for tumor detection is a very dynamic procedure that allows for the right treatment at the right time [2]. In particular, knowledge-based techniques, Fuzzy Clustering means, K-means, artificial neural networks, support vector machines, and expectation-maximization (EM) algorithm techniques are the most common methodologies used in the region-based segmentation to obtain the necessary information data from all types of medical imaging [4]. Several of these methods have been used to detect tumors in MRI data. [3].

Modern digital imaging technology has advanced over the last decade, focusing on the artificial learning and deep learning approaches [2]. Image identification, detection, and classification, image tracking and facial recognition, statistical analysis and assessment study of films, pattern recognition, and signal processing of robots and machines are all examples of areas where it is now applied [5]-[6]. Most machine learning systems require an image to be intelligently segmented, clarify the basics of images, and allow for a faster and simplest study of each pixel [7]. To determine exactly what actual-world feature is conveyed by each pixel of an image, modern image segmentation techniques employ machine learning models[8].

Many artificial methods use hand-crafted characteristics [2] like edges, corners, regression and gradient histogram, discrete regional sequence, etc. [9]. The emphasis was on executing a standard machine learning workflow in these approaches: first, extract the targeted features and then send them to a classifier. In such a way, the classifier training protocol is not influenced by the existence of the specific characteristics.

Damodharan and Raghavan[10] proposed a neural network-based identification and classification technique for brain tumor identification by MRI. The quality rate of this method for segmentation of the white matter (WM), gray matter (GM), cerebrospinal fluid (CSF), and tumor area is reported to be 83 percent [10].

A classifier protocol based on the use of the Steerable Wavelet Machines (SWM) technique was proposed by Alfonse and Salem for the automated brain tumor detection [11]. The feature is obtained through the Fast Fourier Transform (FFT) algorithm to enhance the classifier performance, and feature reduction is achieved using Minimal-Redundancy-Maximal-Relevance (MRMR) approach. The accuracy of this classifier algorithm is over 90% [11].

Convolution Neural Networks (CNN) approach-based segmentation [12] was applied to natural montage labeling in computer vision. Neural Network is a term chosen due to a similarity of the main principle to the biological neuron network: basic elements are identical and interconnected [37]. The RGB networks of a color image test version are the inputs to the model in this case. Pinheiro and Collobert [13] utilize a simple CNN method that makes accurate predictions of each segment and further enhances predictions by using them as additional information in a second CNN model data.

Other research involves processing the images of various resolutions by several distinct convolutional neural networks. By combining the information learned from all convolutional neural networks, the final classification approximation is generated in every pixel of an image. A uniform optimization of the image can be achieved using a more regional, megapixel clustering [14]-[15].

Dong et al. developed a fully automatic U-Net-based methodology of deep convolution networks for the brain tumor segmentation [16]. The studies were performed on the BRATS 2015 database data sets, comprising low-grade glioma (LGG) and high-grade glioma (HGG) patients. The methodology has been tested using a five-fold cross-validation method. Using this approach, it is possible to construct a model for segmenting tumor images without intervening with particular clinicians.

Hawaii et al. developed an automated method for brain tumor detection based on the deep neural networks (DNN) [3]. The created deep neural network technique uses both global and local contextual data at the same time [3]. The problems with the tumor label mismatch are removed using a two-phase training technique.

We introduce a similar approach based on a multilayer deep neural network (MDNN) to identify, segment, and classify brain tumors. MATLAB implements the proposed system that consists of the following main sections: A) image pre-processing; B) image segmentation using Otsu thresholding and morphological operations; C) Discrete Wavelet Transform is used to extract features (DWT); D) image classification using SVM. In addition, we evaluate multiple options for the best training of Deep Neural Networks (DNNs). Segmentation performance is increased, and the wider database can be handled. Finally, the experimental results of the MRI segmentation and classification are analyzed and compared based on several functional constraints.

2. THE PROPOSED APPROACH

The proposed approach utilizes DNN to identify, segment, and classify brain tumor MR images. We have used MATLAB 17b software to implement this proposed technique. While implementing the approach, the two classes of the brain tumor MRI datasets are considered. A medium filtering algorithm was used at the initial stage of pre-processing. The second phase was segmentation performed by Otsu thresholding and morphological operations. The third phase was feature extraction performed by DWT, and MDNN carried out the final classification. The flow diagram of the framework can be seen in Figure 1.

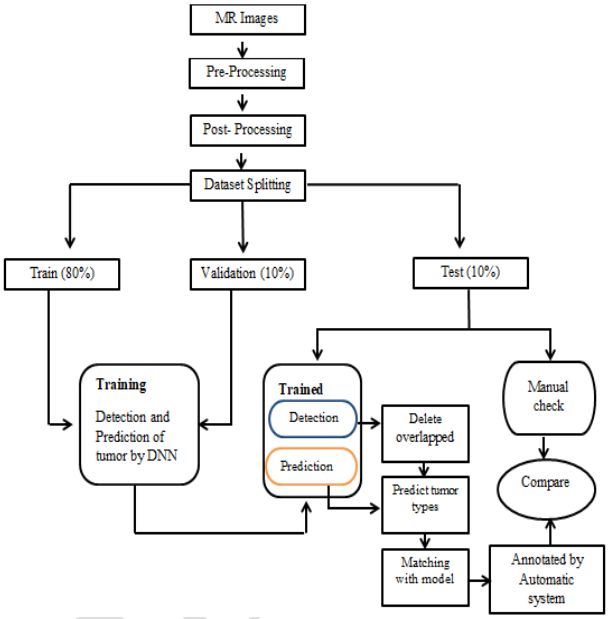

Figure 1: The suggested Framework's flow diagram.

2.1 Preprocessing Phase

Before performing any image processing, exclude any extraneous data from the image [17]. Consequently, image pre-processing should be the primary step. Pre-processing can include three procedures: gray image conversion, noise reduction, and image reconstruction of images[17][18]. The most popular pre-processing method is the conversion to a grayscale image. Once the painting is transformed to grayscale, specific filtering methods can be used to remove any excessive noise [19]. Gaussian, average, and linear filters can decrease noise in the image [11]. We used the median filter due to its high noise sensitivity in our case.

2.2 Segmentation Phase

Due to the huge number of images usually obtained during medical imaging [21], medical specialists can't classify the acquired images in a reasonable time manually. That is why an image segmentation is necessary, providing the division of the image into several non-overlapping areas[20]. Segmentation converts the images into pixel sets that are more meaningful and simpler to examine. It's used to locate the image's limits or fragments; all the segmented fragments define a whole image. Similarity and discontinuity are the two fundamental features of image segmentation [23]. Multiple segmentation methods are commonly used, like threshold-based segmentation, histogram-based methods, region-based methods (regional growth, splitting, and merging), edge-based and clustering methods (expectation-maximization, k-means, FCM, and mean shift)[22][23]-[25]. Otsu thresholding and morphological segmentation techniques have been applied in our method for tumor diagnosis and tumor region determination in MRI images.

2.3 Feature Extraction algorithm

The feature extraction is an important phase in any pattern classification; it provides useful information that describes each pattern class. [26]. Feature vectors are created by extracting relevant properties from images [27]-[28]. The classifier method then uses these feature vectors to determine the target output unit input data. When processing the extracted features, it becomes simpler for all the classifiers to differentiate between various classes. Extracting the most important information from raw data is known as feature extraction[27]. The extraction in our study is based on the Discrete Wavelet Transform (DWT) technique. Feature extraction can be useful in recognizing the exact position of the brain tumor; its use makes it easier to predict the next phase of image processing. Texture and Intensity, Entropy, Energy, DMI, Correlation, Homogeneity, and other properties are extracted using DWT.

2.4 Classification of features

Classification of the extracted features is essential to categorize every object into one of the predefined classes or groups in the data set. In other words, classification is an important method frequently used to distinguish between normal brain and tumor images [29]. It is a data acquisition feature that assigns objects to target classes or categories in a dataset [30]. The data analysis algorithm is used to classify cancers so that generic tumor markers may be predicted. This study used a support vector machine (SVM) classifier and a convolutional neural network to categorize the data.

a. Support Vector Machine (SVM):

SVMs consist of compatible supervised classification and regression learning methods. The affiliate to a family of linear classifications[31]. SVM minimizes the error of quantitative classification and, at the same time, optimizes the geometric margin. SVM also reduces the structure of classification approaches [32]. It extends input vectors to a multidimensional field, where a maximum hyper frame is created. On each side of the hyperplane, two hyper frames are designed for data splitting. The hyper-plane is separated to increase the distance between the two parallel hyper frames. The classifier's generalization error will be more accurate if the margin between the SVM similar hyper frames is larger [33]. In the proposed methodology, the SVM approach and the deep neural network algorithm positively classify benign and malignant brain tumors.

b. Multilayer Feed Forward Deep Neural Network

Neural Networks are non-linear arithmetical data processing techniques used to construct complex input-output connections or find patterns in the data. Data warehousing companies use Neural Networks to extract data from databases in the process known as knowledge discovery or data mining [34][35]. Multilayer Deep Neural Network is one of the simplest Feed Forward Neural Networks used for classification purpose [36]. The classification applies to the data processing process and can identify image patterns. Training of tumor image databases is achieved by assigning different properties to multiple layers of Deep Neural Networks. The subsequent layer in the network is fed by the input layer that receives the data. Each next layer is trained by a different set of features based on the performance of the previous layer[38]. The more complex features the layer can identify, merging and recombining features of the prior layer, the deeper the neural network is. The Deep Neural Network consists of the following three main parts in this work.

Training: The process of passing the same data through the network is considered training. In the training set, we processed the same database repeatedly, repeating each stage (epoch) and continuing to learn about the features of these data. The predictions are made based on the obtained training data. The weights are successfully optimized in the proposed approach. These weights are iteratively updated and moved towards their optimal values due to training. Optimization algorithm Stochastic gradient descent (SGD) is used for optimization, being chosen due to its high efficiency [11].

Validation: In addition to the training data, we employed a data collection known as the validation set to validate our DNN model, providing information to change our hyperplanes. During validation, the model classifies each input from the training set based on what it is trained for. The validation data set is not the same as the training set; it does not include training data that the model is already familiar with. We performed the validation to avoid the training set over-fitting, which we decreased with the help of regularization.

Testing: After validating the DNN model, we used a data set known as a testing set (different from training and validation sets) to test the model. In the testing set, our model was used to predict the output of the unlabeled data after training and validation.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed DNN methodology was applied to two MRI images of benign and malignant tissue database sets. For training, validation, and testing, images from two databases were separated into training, validation, and testing groups. Both Class 1(benign) and Class 2 (malignant) databases include 747 MRI brain images, 80% of which were selected for training, 10% for validation, and 10% for testing. The features of images were obtained via the multilayers deep neural network. The efficiency of the proposed method was evaluated in terms of matrix correlation, entropy and connectivity, number of objects, and iteration number. When considering the overall neural network design, it is critical to define the number of hidden layers and the number of neurons in the hidden layers. The DNN model we designed consists of 31 input layers, 7 hidden layers, and 2 output layers. The

number of neurons in hidden layers was calculated using the following equations (r stands for a total number of neurons):

$$r = \left(\left({}^{n.input}/_{n.output}\right)^{\frac{1}{8}}\right) \quad \text{Eq. (1)}$$

$$Layer1 = n.output * r^7 \quad \text{Eq. (2)}$$

$$Layer2 = n.output * r^6 \quad \text{Eq. (3)}$$

$$Layer3 = n.output * r^5 \quad \text{Eq. (4)}$$

$$Layer4 = n.output * r^4 \quad \text{Eq. (5)}$$

$$Layer5 = n.output * r^3 \quad \text{Eq. (6)}$$

$$Layer6 = n.output * r^2 \quad \text{Eq. (7)}$$

$$Layer7 = n.output * r \quad \text{Eq. (8)}$$

Otsu binarization and morphological techniques were performed to segment the MR images presented in Fig.2. The effectiveness of brain tumor segmentation and localization was reported to be 98 percent, based on the comparison with tissue analyzed data.

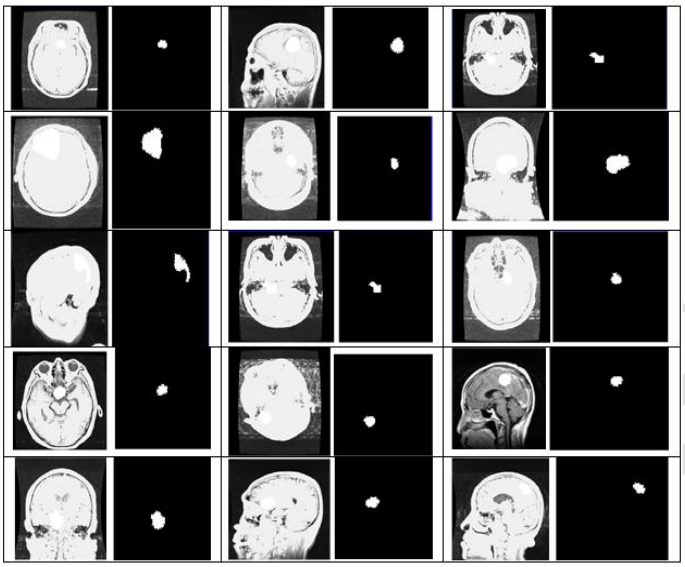

Figure 2: Segmented MR Brain tumor images

The overall performance of the proposed technique for both classes of tested images was evaluated in terms of accuracy, sensitivity, and specificity as defined in the equations below and shown in Table 1.

$$\text{Specificity} = \left[\frac{\text{True positive (TP)}}{(\text{True positive (TP)} + \text{False positive (FP)})}\right],$$

$$\text{Sensitivity} = \left[\frac{\text{True positive (TP)}}{(\text{True positive (TP)} + \text{False negative (FN)})}\right],$$

$$\text{Accuracy} = \left[\frac{(\text{TP}) + (\text{TN})}{((\text{TP}) + (\text{TN}) + (\text{FP}) + (\text{FN}))}\right];$$

Where,

$$\text{True positive (TP)} = \frac{No\ of\ resulted\ \ tumor\ \ images}{totlal\ \ No\ of\ \ images}$$

$$\text{True Negative (TN)} = \frac{No\ of\ non-tumor\ \ images}{totlal\ \ No\ of\ \ images}$$

$$\text{(FP)} = \frac{Noofnon\ -tumorimagesbutdetectedpositive}{totlalNoofimages}$$

$$\text{(FN)} = \frac{No\ of\ tumor\ \ images\ \ but\ \ detected\ \ negitive}{totlal\ \ No\ of\ \ images}.$$

Table 1: The Accuracies based Comparison of two classes

Number of test images (Class 1 = 370, Class 2 = 375)							
Training Confusion (80 %)							
Data sets	TP	TN	FP	FN	Specificity	Sensitivity	Accuracy
Class 1	47	0	0	3.3	100	93.5	93.5
Class 2	46.3	0	0	3.4	100	93.1	93.1
Validation Confusion (10%)							
Data sets	TP	TN	FP	FN	Specificity	Sensitivity	Accuracy
Class 1	44.6	0	0	3.6	100	92.6	92.6
Class 2	48.2	0	0	3.6	100	93.1	93.1
Testing Confusion (10%)							
Data sets	TP	TN	FP	FN	Specificity	Sensitivity	Accuracy
Class 1	42	0	0	2.6	100	94.1	94.1
Class 2	47.3	0	0	4.9	100	90.1	90.1
Overall System Confusion							
Data sets	TP	TN	FP	FN	Specificity	Sensitivity	Accuracy
Class 1	46.1	0	0	3.5	100	93.5	93.5
Class 2	46.7	0	0	3.7	100	93.2	93.2

The error histogram (Fig.4), as well as the training, validation, and testing results (Fig.2), illustrate the method's improved performance. Gradient drop is multiplied by negative drop, indicating shifts in biases and weights (Fig.3). As Fig.3 also shows, the learning rate is low, resulting in a stable algorithm. Validation performance shows the relationship between the output and the target and the maximum validation indicates the perfect training of the target (image-based tumor detection) (Fig.5).

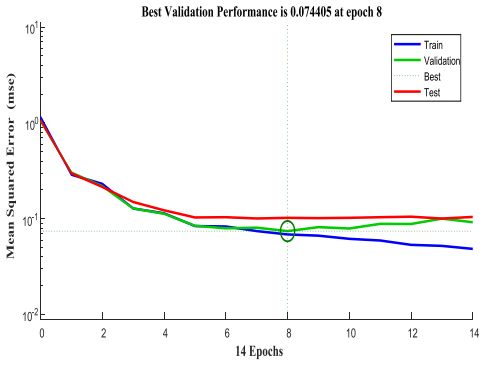

Figure 3: MDNN Training Performance

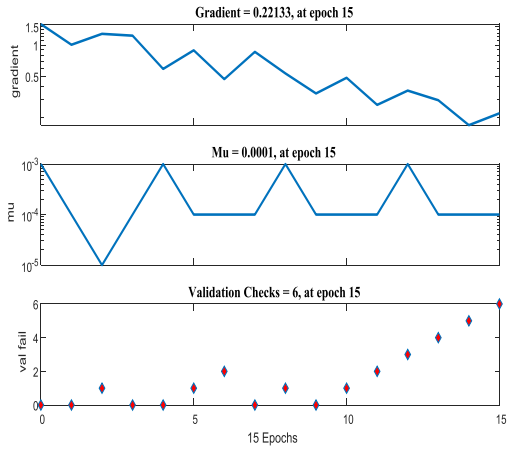

Figure 4: MDNN Gradient Performance

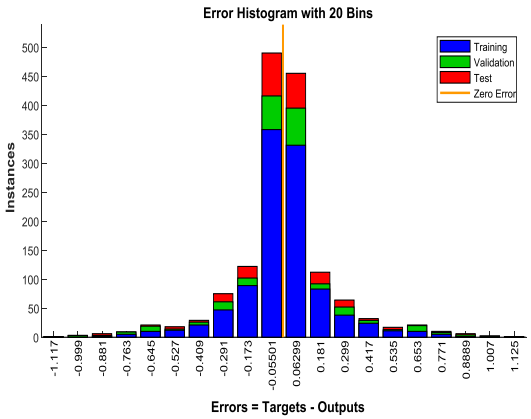

Figure 5: MDNN Error Histogram

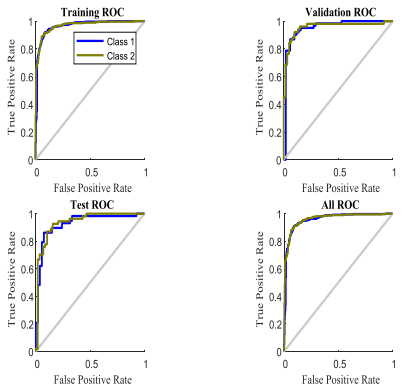

Figure 6: MDNN ROC result of training, validation, and testing

Statistical properties of the feature extraction and the classifier for the processed images are shown in Tables 2 and 3.

Table 2: Statistical properties of different MR images

Image	Mean	Std.d..	Entropy	RMS	IDM	Variance
Image1	0.0038	0.0892	2.78234	0.08934	0.26	0.008
Image2	0.0030	0.0891	2.99465	0.08922	0.10	0.008
Image3	0.0051	0.0896	2.90444	0.08980	2.39	0.008
Image4	0.0027	0.0897	2.65355	0.08979	1.58	0.008
Image5	0.0037	0.0897	2.77178	0.08980	0.86	0.008
Image6	0.0038	0.0897	3.15355	3.15355	-0.34	0.008
Image7	0.0024	0.0897	2.90384	0.08980	-0.61	0.008
Image8	0.0051	0.0896	2.90445	0.08980	2.39	0.008
Image9	0.0029	0.0897	2.83886	0.08980	-0.14	0.008
Image10	0.0020	0.0897	3.22174	0.08980	0.67	0.008
Image11	0.0041	0.0897	2.84742	0.08980	1.57	0.008
Image12	0.0056	0.0896	2.88226	0.08980	1.07	0.008
Image13	0.0050	0.0896	3.14888	0.08980	-0.23	0.008
Image14	0.0031	0.0897	3.11201	0.08980	0.90	0.008
Image15	0.0026	0.0897	3.03799	0.08980	0.43	0.008

Table 3: Result of Classifier at different cases

Image	Iteration	Time	Performance	Gradient	Regression	Validity
Image1	18	8s	0.769	0.895	0.0731	6
Image2	16	6s	0.655	1.39	0.0338	6
Image3	19	8s	0.0475	0.103	0.0832	6
Image4	15	6s	0.0378	0.230	0.0911	6
Image5	15	6s	0.0324	0.522	0.03755	6
Image6	16	6s	0.0283	0.909	0.0951	6
Image7	26	10s	0.0220	0.0456	0.0708	6
Image8	17	6s	0.0282	0.738	0.0711	6
Image9	14	6s	0.0426	0.399	0.08313	6
Image10	18	7s	0.0271	0.896	0.07572	6
Image11	14	5s	0.0484	0.535	0.07217	6
Image12	15	5s	0.0438	0.0714	0.06987	6
Image13	12	4s	0.0500	0.0830	0.11672	6
Image14	15	6s	0.0316	0.0616	0.076063	6
Image15	15	6s	0.0407	1.20	0.06964	6

4. CONCLUSIONS

This article proposed using a multilayer deep neural network for brain tumor identification, segmentation, and classification. The goal was to develop a tool to differentiate malignant and benign tumors, which would assist decision-making during the medical evaluation. Automated classification and segmentation were among the main aims of the applied MDNN. The suggested technique consists of several phases (training, validation, and testing) and includes segmentation, detection, and classification of MR images. The automated segmentation algorithm precisely provides tumor shape, size, and location, as well as image properties such as connectivity and entity number. Using the matrix of mean, correlation, and entropy, the main parameters of the tumor can be determined. The proposed strategy is promising because the implementation of a classifier successfully reduced computing

time and the number of iterations. The validation Feature was achieved to be maximally possible. The 93 percent accuracy implies that the proposed approach for identifying and classifying benign and malignant tissues using MR images is acceptable. The developed method is suggested to be convenient for radiologists or other medical doctors to introduce decision support systems in clinics. In the future, the proposed technique will be applied by us to other medical imaging modalities, such as CT and Positron Emission Tomography (PET), in both 2D and 3D schemes.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that no competing interests exist. The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

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