Classification using Deep Neural Network and Convolutional Neural Network for Brain Tumors

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Abstract : Brain tumor classification is a challenging task in the field of medical image processing. Early detection brain tumor can increase patient's survival rate. Various machine learning techniques has been proposed to classify the tumor region areas that are segmented from brain images as benign and malignant. A brain tumor detection method based on Deep Neural Network (DNN) was introduced. In this method, the collected Magnetic Resonance Imaging (MRI) images were segmented by Fuzzy C-Means clustering technique. Then, the features were extracted from the segmented images using Discrete Wavelet Transform (DWT) technique and the dimensionality of the features was reduced by applying Principal Component Analysis (PCA). Finally, DNN was applied for brain tumor detection. In order to improve the brain tumor detection accuracy, DNN with Convolutional Neural Network (DNN-CNN) is introduced in this paper for brain tumor detection. In DNN-CNN, the convolutional layers, pooling layer and fully connected layer are used to refine the brain tumor image classification. The convolutional layer aims to learn feature representations of the input image. The pooling layer reduces the number of connection between convolutional layers. The fully-connected layers take all neurons in the previous layer and connect them to every single neuron of current layer to generate global semantic information. The CNN is used to learn the feature representation and these features are used in the hidden layer of DNN and the image classification output is generated in the output layer of DNN. The experiments are conducted in different MRI images to prove the efficiency of CNN-DNN based brain tumor detection in terms of accuracy, precision, recall and f-measure.

***IndexTerms* - Brain tumor detection, Deep Neural Network, Convolutional Neural Network, Fuzzy C Means, Discrete Wavelet Transform.**

I. INTRODUCTION

A very difficult task for radiologists is early detection of brain tumor (Amin et al, 2017). Brain tumor raises very fast, its average size doubles in just twenty-five days. If not treated properly, the survival rate of the patient is normally not more than half a year. It can rapidly lead to death. Because of this reason, an automatic system (Devi & Bhattacharyya, 2018) is required for brain tumor detection at an early stage. The automatic detection of brain tumor has to easily differentiate between cancerous and non-cancerous brain images.

One of the best imaging techniques for brain tumor detection is MRI. It used for modeling the tumor progression in both treatment and detection phases. Various automated approaches have been proposed for brain tumor detection and type classification using MRI images. But, SVM (Vani et al, 2017) and Neural Network (NN) (Kadam, 2012) are widely used approaches for brain tumor detection. Nowadays, deep learning models set an exciting trend in machine learning as the deep learning can efficiently represent complex relationships without requiring large number of nodes. Because of this reason deep learning grew rapidly to become the state of the art in different health informatics areas such as medical image analysis, bioinformatics and medical informatics.

A deep learning technique DNN (Mohsen et al, 2018) was applied for automated brain tumor classification using brain MRI images. A set of features from the collected images were extracted from the segmented MRI images by using Discrete Wavelet Transform (DWT). The extracted features are trained in the DNN to differentiate normal images and some types of brain tumors such as glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors. In this paper, DNN-CNN is introduced to improve the brain tumor detection accuracy. In the input layer of the DNN, the convolutional layer, pooling layer and fully-connected layer of CNN is processed for better feature representation. Then, these features are processed in the hidden layer and output layer for brain tumor detection. Thus, the brain tumor detection accuracy is improved by using better feature representation.

II. LITERATURE SURVEY

Zhang et al. (2011) proposed a Neural Network (NN)-based method for classifying the given MRI brain images as normal or abnormal. Initially, wavelet transform was employed for extracting the features from images and the Principal Component Analysis (PCA) was used for reducing the features dimensions. Then, the reduced features were fed to the BPNN in which Scaled Conjugate Gradient (SCG) was adopted to discover the optimal weights of the NN. However, the feature extraction phase was the most time-consuming process.

Jafari & Kasaei (2011) proposed a NN-based method for automatic classification of MRI of brain under three classes such as normal, lesion benign and malignant. In the pre-processing phase of this method, the enhancement and restoration techniques were used for providing a more suitable image for the subsequent processes. The seeded region growing segmentation was used for splitting the image into significant regions. Then, each pixel was labeled and the features were extracted using the DWT. After that, the dimension of the extracted DWT features was reduced by using the PCA for obtaining more significant features. At last, a supervised feed-forward Back-Propagation (BP) NN was used for classifying the subjects to normal or abnormal. However, it requires new training for each time whenever there was an increase in image database.

Kalbkhani et al. (2013) proposed a robust algorithm for detecting the type of diseases in brain MRI. Initially, two-level 2D WT of input image was computed and the wavelet coefficients of detail sub-bands were modeled by Generalized Autoregressive Conditional Heteroscedasticity (GARCH) statistical model. The parameters of this model were considered as the primary feature vector. Once the feature vectors were normalized, PCA and LDA were used for extracting the appropriate features and eliminating the redundancy from the primary feature vector. At last, the extracted features were applied to the K-Nearest Neighbor (KNN) and SVM for classifying the normal image or disease type. However, the classification algorithms consume more time for training.

Sahu et al. (2015) proposed a new approach for classifying normal and abnormal brain MRI by using Bi-dimensional Empirical Mode Decomposition (BEMD) and Autoregressive (AR) model. Initially, brain MRI was decomposed into four Intrinsic Mode Functions (IMFs) by using BFMD and AR coefficients from multiple IMFs were concatenated for constructing a feature vector. Then, a binary classifier such as Least-Squares SVM (LS-SVM) was applied to classify the brain MRI as normal or abnormal. However, the kernel parameters used in this method were chosen based on the trial and error method. It requires an automatic selection of kernel parameters and kernel function to increase the classification accuracy while a large database was used.

Wang et al. (2016) proposed a deep Convolutional NN (CNN) for segmenting the MRI brain images. In this method, three networks such as network of $2x$ upsampled prediction, network of $4x$ upsampled prediction and network of 8x upsampled prediction were constructed. The datasets was obtained from IBSR database of Neuroimaging Informatics Tools and Resources Clearinghouse (NITRC). However, these datasets were not very effective since it has only T1 images. For T1 images, this method was not effective.

III. Proposed Methodology

In this section, the proposed CNN-DNN based brain tumor detection is described in detail. Initially, a dataset consists of 66 real human brain MRIs with 22 normal and 44 abnormal images is collected. Then, the CNN-DNN based brain tumor detection is processed which consists of different processes are image segmentation, feature extraction and reduction and classification.

3.1 Image Segmentation

Image segmentation is the process of separating the different normal brain tissues such as Gray Matter (GM), White Matter (WM) and CerebroSpinal Fluid (CSF) and the skull from the tumor tissues in brain MR images as the resulted segmented tumor part only would be used in the next steps. With the development of fuzzy theory, the FCM forms the clusters based on the distance between the data points (images) and the cluster centers are formed for each cluster. FCM is a data clustering technique in which a data set is grouped into n clusters with every data point in the dataset related to every cluster and it will have a high degree of belonging (connection) to that cluster and another data point that lies far away from the center of a cluster which will have a low degree of belonging to that cluster. After each iteration membership and cluster centers are updated according to the following formula:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\left(\frac{2}{m-1}\right)}} \quad (1)$$

$$v_j = \frac{\left(\sum_{i=1}^{n}(\mu_{ij})^m x_i\right)}{\left(\sum_{i=1}^{n}(\mu_{ij})^m\right)}, \forall j = 1,2, \dots c \quad (2)$$

In Eq. (1) and Eq. (2), n is the number of images, $v_j$represents the jth cluster center, m is the fuzziness index, c represents the number of cluster center, μ_{ij} is the membership of ith image to the jth cluster center and d_{ij} is the Euclidean distance between ith and jth cluster center.

The main intention of FCM is to minimize

$$J(U,V) = \sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^m \left\|x_i - v_j\right\|^2 \quad (3)$$

In Eq. (3), $\left\|x_i - v_j\right\|^2$is the Euclidean distance between ith image and jth cluster center.

FCM clustering algorithm

Let $X = \{x_1, x_2, \dots x_n\}$be the set of images and $V = \{v_1, v_2, \dots v_n\}$ is the set of centers.

1. Randomly select c cluster center.
2. Calculate the fuzzy membership μ_{ij} using Eq. (1).
3. Compute the fuzzy centers v_j using Eq. (2)
4. Repeat the step 2 and 3 until the minimum J value is achieved.

3.2 Feature Extraction and Reduction

After the image segmentation process, the features are extracted using DWT. DWT has the advantage of extracting the most relevant features at different directions and scales as they provide localized time-frequency information of a signal using cascaded filter banks of high-pass and low-pass filters to extract features in a hierarchy manner. A 2-levels DWT decomposition of an image is used where the functions h(n) represent the coefficients of high-pass filters and g(n) represent the coefficients of the low-pass filters. As a result, there are four sub-band (LL, LH, HH, HL) images at each level. The LL subband can be regarded as the approximation component of the image, while the LH, HL, HH subbands can be regarded as the detailed components of the image. In this proposed work, 3-levels decomposition of Haar wavelet is used to extract $32 \times 32 = 1024$ features for each brain MRI. Then, PCA is applied to reduce the number of features for further process.

3.3 Classification

The extracted features are given as input to the CNN-DNN for image classification. CNN consists of three layers are convolutional, pooling and fully-connected layer. The convolutional layer aims to learn feature representation. Convolutional layer is composed of several convolution kernels which are used to compute different maps. Generally, each neuron of a feature map is connected to a region of neighboring neurons in the previous layer. The new feature map is obtained by first convolving the input with a learned kernel and then applying an element-wise nonlinear activation function on the convolved results. The shared by all spatial location of features to generate each feature map. By using several different kernels, the complete feature maps are obtained. The feature value at location (i, j) in the k-th feature map of l-th layer, $z_{i,j,k}^{l}$ is calculated as follows:

$$z_{i,j,k}^{l} = \left(w_k^l\right)^T F_{i,j}^{l} + b_k^l \tag{4}$$

In Eq. (4), w_k^l is the weight vector of the k-th filter of the l-th layer, b_k^l is the bias terms of the k-th filter of the l-th layer and $F_{i,j}^{l}$ is the extracted features centered at location (i, j) of the l-th layer. An activation function of CNN introduces nonlinearities to CNN, which are desirable for multi-layer networks to detect nonlinear features. Consider $a(.)$ is the nonlinear activation function. The activation value $a_{i,j,k}^{l}$ of convolutional feature $z_{i,j,k}^{l}$ can be computed as,

$$a_{i,j,k}^{l} = a\left(z_{i,j,k}^{l}\right) \tag{5}$$

The pooling layer aims to achieve shift-invariance by reducing the resolution of the feature maps. This layer is usually placed between two convolutional layers. Each SURF map of a pooling layer is connected to its corresponding SURF, OLPP, HOG, WLBP, HFO and HFD map of the preceding convolutional layer. For each feature map $a_{:,:,k}^{l}$ the pooling function $pool(.)$ is given as:

$$y_{i,j,k}^{l} = pool\left(a_{m,n,k}^{l}\right), \forall (m, n) \in \mathcal{R}_{ij} \tag{6}$$

In Eq. (6), $\mathcal{R}_{ij}$ is a local neighborhood around location (i, j). The kernels in the first convolutional layer are designed to detect low-level features, while the kernels in higher layers are learned to encode more abstract features. By stacking various convolutional and pooling layers, gradually extract higher-level feature representations. After several convolutional and pooling layers, there may be one or more fully-connected layers which aim to perform high-level reasoning. The fully-connected layers take all neurons in the previous layer and connect them to every single neuron of current layer to generate global semantic information. The output of the fully connected layer is given as input to the hidden layer of DNN. DNN consists of multiple hidden layers which can handle the huge volume of data. Each hidden layer of DNN is defined as sigmoid transfer function which is given as follows:

$$f(x) = \frac{1}{1+e^{-x}} \tag{7}$$

The output layer of DNN is described by the following equation.

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b_i\right) \tag{8}$$

In Eq. (8), y is the output neuron value; $f(x)$ is the transfer function, w_i refers the weight values, x_i denotes input data values and b_i refers to the bias value. Based on the output neuron values, the relationship between countermeasures and the features is learned which detects the brain tumour. By using this learned model, the brain tumour is detected.

CNN-DNN Algorithm

Input: Training dataset $D = \{(x_1, y_1), (x_2, y_2), \dots (x_n, y_n)\}$
//x_n is the feature vectors, y_n is the output (presence or absence of brain tumour)
Output: Trained neural network
Initialize all weights and biases in network;
$while(termination\ condition\ is\ not\ satisfied)$
{
    $for(each\ training\ parameter\ X\ in\ D)$
    {
        $for(each\ input\ layer\ node\ j)$
        {
            Process the convolutional layer using Eq. (4) and (5)
            Process the pooling layer using Eq. (6)
            Process the fully connected layer
    $for(each\ hidden\ or\ output\ layer\ node\ j)$

$$H_j = \frac{1}{1+e^{-j}};$$

$$O_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right)$$

        $for(each\ node\ j\ in\ output\ layer)$

$$E_j = \frac{1}{2}\left(t_j^p - o_j^p\right)^2$$

//t_j^p is the desired target output for the p-th observation and the o_j^p is the actual output for the p-th observation.

```
    Update the weight and bias values based on the E_j (error value).
                    }
            }
}
    if O_j < 0.5
    {
        return -1 // it is corresponding to normal image (i.e., absence of brain tumour)
    else
        return 1 //it is corresponding to abnormal image (i.e., presence of brain tumour)
    }
```

IV. RESULT AND DISCUSSION

In this section, the performance of DNN and CNN-DNN based brain tumor detection methods are tested using MATLAB 2017b in terms of accuracy, precision, recall and f-measure. For the experimental purpose, a dataset consists of 66 real human brain MRIs with 22 normal and 44 abnormal images is used.

4.1 Accuracy

Accuracy is the fraction of the total number of correct brain tumor detections to the actual dataset size. It measures the overall rate of correctly detected brain tumor in brain MRIs.

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)}$$

where, TP is the percentage of abnormal images (i.e., affected by brain tumor) in the training dataset that are correctly classified as abnormal image, TN is the percentage of normal image (i.e., absence of brain tumor) in the training dataset that are correctly classified as normal image, FP is the percentage of normal images that are incorrectly classified as abnormal image, FN is the percentage of abnormal images that are incorrectly classified as normal image.

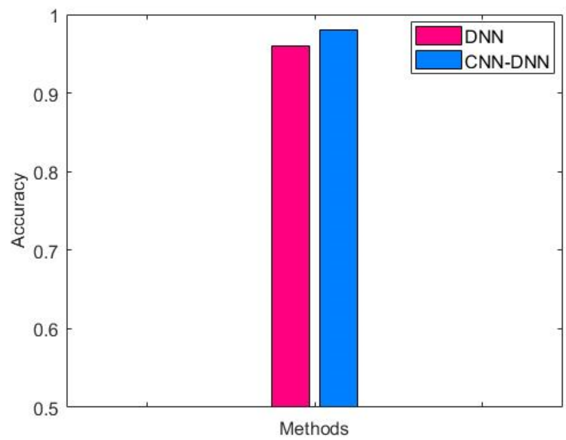

Fig.1 Comparison of Accuracy

Figure 1 shows the accuracy between DNN and CNN-DNN based brain tumor detection. X-axis denotes the brain tumor detection methods and Y-axis denotes the accuracy value. From Figure 1 it is proved that the proposed CNN-DNN based brain tumor detection method has high accuracy than DNN based brain tumor detection method.

4.2 Precision

Precision measures the exactness of the classifier, i.e., what percentage of images that the classifier labeled as abnormal images and it is given by,

$$Precision = \frac{TP}{TP + FP}$$

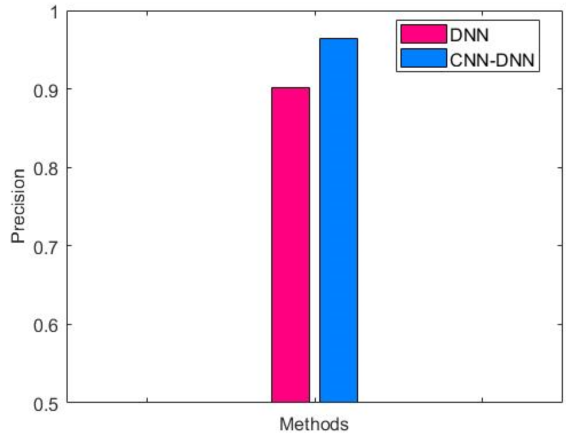

Fig.2 Comparison of Precision

Figure 2 shows the precision between DNN and CNN-DNN based brain tumor detection. X-axis denotes the brain tumor detection methods and Y-axis denotes the precision value. From Figure 2 it is proved that the proposed CNN-DNN based brain tumor detection method has high precision than DNN based brain tumor detection method.

4.3 Recall

Recall measures the completeness of the classifier results, i.e., what percentage of abnormal images did the classifier label as abnormal, and is given by

$$Recall = \frac{TP}{TP + FN}$$

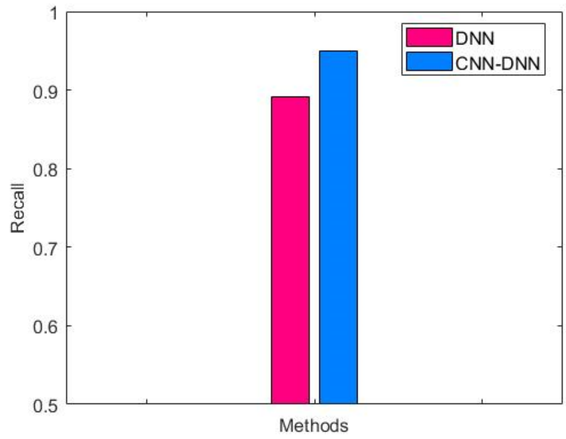

Fig.3 Comparison of Recall

Figure 3 shows the recall between DNN and CNN-DNN based brain tumor detection. X-axis denotes the brain tumor detection methods and Y-axis denotes the recall value. From Figure 3 it is proved that the proposed CNN-DNN based brain tumor detection method has high recall than DNN based brain tumor detection method.

4.4 F-measure

F-measure is computed as the harmonic mean of the precision and recall. It is calculated as,

$$F - measure = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

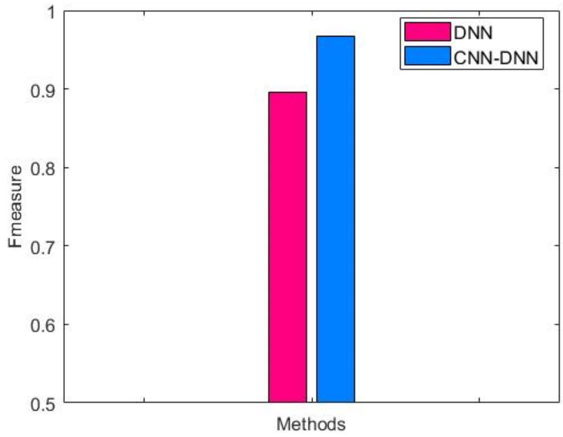

Fig.4 Comparison of F-measure

Figure 4 shows the F-measure between DNN and CNN-DNN based brain tumor detection. X-axis denotes the brain tumor detection methods and Y-axis denotes the F-measure value. From Figure 4 it is proved that the proposed CNN-DNN based brain tumor detection method has high F-measure than DNN based brain tumor detection method.

V. CONCLUSION

In this paper, CNN-DNN based brain tumour detection is for efficient detection of brain tumour. Initially, a dataset which consists of normal and abnormal brain MRI images are collected and then the FCM technique is applied for image segmentation. It separates the different normal brain tissues such as GM, WM and CSF and the skull from the tumour tissues in brain MRI. After segmenting the brain images, the features are extracted from it by using DWT. The extracted features are processed by the convolutional layer of CNN which learns the feature representation and then pooling layer is processed it reduces the number of connection between convolutional layers. The fully-connected layer takes all neurons in the previous layer and connects them to every single neuron of current layer to generate global semantic information. The output of the fully-connected layer is processed by the hidden layer of the DNN and finally in the output layers brain tumor is detected. The experimental results prove that the proposed CNN-DNN based brain tumor detection method has high accuracy, precision, recall and f-measure than DNN-based brain tumor detection method.

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