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Classification using deep learning neural networks for brain tumors

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Abstract

Deep Learning is a new machine learning field that gained a lot of interest over the past few years. It was widely applied to several applications and proven to be a powerful machine learning tool for many of the complex problems. In this paper we used Deep Neural Network classifier which is one of the DL architectures for classifying a dataset of 66 brain MRIs into 4 classes e.g. normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors. The classifier was combined with the discrete wavelet transform (DWT) the powerful feature extraction tool and principal components analysis (PCA) and the evaluation of the performance was quite good over all the performance measures.

Keywords: Machine learning; Deep learning; Deep neural network; Discrete wavelet transform; Principle component analysis; Fuzzy c-means; Magnetic resonance images

1. Introduction

Brain is one of the most complex organs in the human body that works with billions of cells. A brain tumor arise when there is uncontrolled division of cells forming an abnormal group of cells around or inside the brain. That group of cells can affect the normal functionality of the brain activity and destroy the healthy cells [1,2]. Brain tumors classified to benign or low-grade (grade I and II) and malignant tumors or high-grade (grade III and IV). Benign tumors are non-progressive (non-cancerous) so considered to be less aggressive, they originated in the brain and grows slowly; also it cannot spread to anywhere else in the body. However, malignant tumors are cancerous and grow rapidly with undefined boundaries. They can be originated in the brain itself which called primary malignant tumor or to be originated elsewhere in the body and spread to the brain which called secondary malignant tumor [3−5].

Brain magnetic resonance imaging (MRI) is one of the best imaging techniques that researchers relied on for detecting the brain tumors and modeling of the tumor progression in both the detection and the treatment phases. MRI images have a big impact in the automatic medical image analysis field for its ability to provide a lot of information about the brain structure and abnormalities within the brain tissues due to the high resolution of the images [3,6−8]. In fact, Researchers presented different automated approaches for brain tumors detection and type classification using brain MRI images since it became possible to scan and load medical images to the computer. However, Support Vector Machine (SVM) and Neural Networks (NN) are the widely used approaches for their good performance over the last few decades [9]. But recently, deep learning (DL) models set an exciting trend in machine learning as the deep architecture can efficiently

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represent complex relationships without requiring a huge number of nodes like in the shallow architectures e.g. SVM and K-nearest neighbor (KNN). For that reason, they grew rapidly to become the state of the art in different health informatics areas such as bioinformatics, medical informatics and medical image analysis [7,9,10].

The contribution of this paper is applying the deep learning concept to perform an automated brain tumors classification using brain MRI images and measure its performance. The proposed methodology aims to differentiate between normal brain and some types of brain tumors such as glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors using brain MRI images. The proposed methodology uses a set of features extracted by the discrete wavelet transform (DWT) feature extraction technique from the segmented brain MRI images, to train the DNN classifier for brain tumors classification.

The structure of this paper is organized as follows: in Section 2 there's an overview on the deep learning concept and architecture, section 3 described the steps of the proposed methodology, section 4 presents the experimental results and discussion and the conclusion and future work is given in section 5.

2. Overview on deep learning

Deep learning (DL) is a subfield of machine learning based on learning multiple levels of representations by making a hierarchy of features where the higher levels are defined from the lower levels and the same lower level features can help in defining many higher level features [11]. DL structure extends the traditional neural networks (NN) by adding more hidden layers to the network architecture between the input and output layers to model more complex and nonlinear relationships. This concept gained the researchers interest in the recent years for its good performance to become the best solution in many problems in medical image analysis applications such as image denoising, segmentation, registration and classification [7,10–13].

There are various DL architectures, convolutional neural networks (CNN) is a common used architecture in recent years that can perform complex operations using convolution filters [7,9,10]. A typical CNN architecture is a sequence of feed-forward layers implementing convolutional filters and pooling layers, after the last pooling layer CNN adopts several fully-connected layers that work on converting the 2D feature maps of the previous layers into 1D vector for classification [10]. Even though the CNN architecture has an advantage of doesn't require a feature extraction process before being applied but training a CNN from scratch is a time consuming and difficult as it needs a very large labeled dataset for building and training before the model is ready for classification which is not always available. Moreover the hardware requirements for processing the large number of filters for the large size of images e.g. 256 × 256 [7,10,14].

Deep Neural Network (DNN) is another DL architecture that is widely used for classification or regression with success in many areas. It's a typical feedforward network which the input flows from the input layer to the output layer through number of hidden layers which are more than two layers [13]. Fig. 1 illustrates the typical architecture for DNNs where Ni is the input layer contains of neurons for the input features, No is the output layer contains neurons for the output classes and Nh,l are the hidden layers.

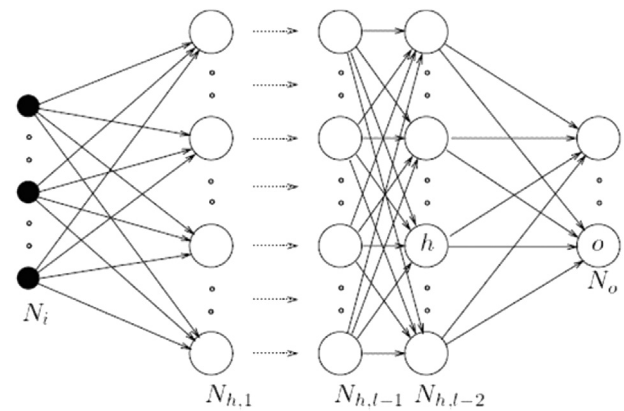


Fig. 1. DNNs architecture.

3. Methodology

Our proposed methodology based on the DNN learning architecture for classification where the classifier is identifying the brain tumors in brain MRIs.

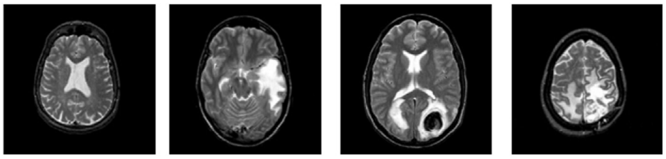
The proposed methodology for classifying the brain tumors in brain MRIs is as follows:

Step 1: Brain MRIs Dataset acquisition
Step 2: Image segmentation using Fuzzy C-means
Step 3: Feature extraction using discrete wavelet transform (DWT) and reduction using Principle component analysis (PCA) technique
Step 4: Classification using DNN

3.1. Data acquisition

According to the World Health Organization (WHO) classification system to identify brain tumors, there are more than 120 types of brain tumors which differ in origin, location, size, characteristics of the tumor tissues [15,16]. In this paper we were concerning with three types of malignant tumors which are:

- Glioblastoma: primary malignant brain tumors that are classified as Grade IV and developed from star-shaped cells, called astrocytes that support nerve cells. It usually starts in the cerebrum.
- Sarcoma: has different grades that vary from grade I to grade IV and it arises in the connective tissues like blood vessels.
- Metastatic bronchogenic carcinoma: secondary malignant brain tumors that was spread to the brain from bronchogenic carcinoma lung tumor.



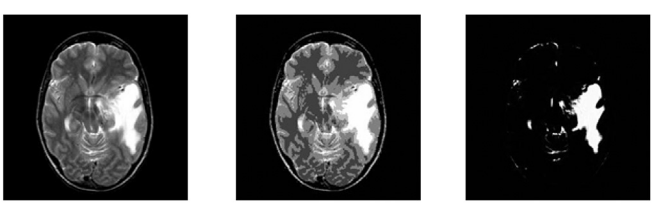
(a) Normal (b) Metastatic bronchogenic carcinoma (c) Sarcoma (d) Glioblastoma

Fig. 2. Brain MRIs dataset sample.

The dataset consists of 66 real human brain MRIs with 22 normal and 44 abnormal images which are glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors collected from Harvard Medical School website (http://med.harvard.edu/AANLIB/) [15]. All the brain MRIs was in axial plane, T2-weighted and 256 × 256 pixel. A sample of the dataset is illustrated in Fig. 2.

3.2. Image segmentation

Image segmentation is the non-trivial task 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 [17] as the resulted segmented tumor part only would be used in the next steps. In this work we used the Fuzzy C-means clustering technique to segment the image into 5 sections as it had good results in our previous work and also for comparison purposes [18]. Fig. 3 shows the results of segmenting a sample image using Fuzzy C-means.



(a) Original image (b) Segmented Image using FCM (c) Segmented tumor using FCM

Fig. 3. A sample image segmented using FCM.

3.3. Feature extraction and reduction

After segmenting the Brain MR images into 5 sections features of the segmented tumor is extracted using discrete wavelet transform (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 [18].

Fig. 4 shows a 2-levels DWT decomposition of an image where the functions h(n) and g(n) represent the coefficients of the high-pass and low-pass filters, respectively. 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 [18,19].

Our methodology utilizes a 3-levels decomposition of Haar wavelet which was also used in our previous work [18] to extract 32 × 32 = 1024 features for each brain MRI. Although this number is not so big compared to the number of feature maps resulted by the convolution filters of CNNs but we used the principal components analysis (PCA) [18] to approximate the original extracted features with lower dimensional feature vectors.

3.4. Classification

After the features are extracted and selected, the classification step using DNN is performed on the resulted feature vector. Classification is performed by using 7-fold cross validation technique for building and training the DNN of 7 hidden layers structure. Also for evaluating the performance of the selected classifier, we employed other machine learning classification algorithms from WEKA [20] using the same criteria. The selected classification algorithms are KNN with K = 1 and 3, Linear discriminant analysis (LDA) and from our previous work [18] SMO-SVM.

4. Experimental results and discussion

The experiment took place using two tools:

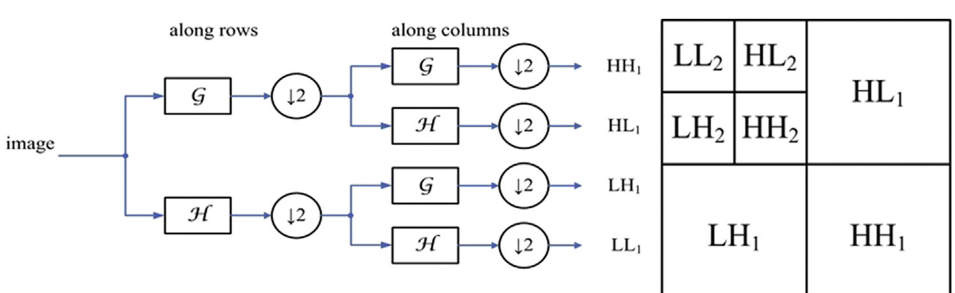


Fig. 4. 2-levels DWT decomposition of an image.

Table 1
Performance of DNN, KNN K = 1 and 3, LDA and SMO classifiers.

Algorithm	Classification rate	Recall	Precision	F-Measure	AUC (ROC)
DNN	96.97%	0.97	0.97	0.97	0.984
KNN K = 1	95.45%	0.955	0.956	0.955	0.967
KNN K = 3	86.36%	0.864	0.892	0.866	0.954
LDA	95.45%	0.955	0.957	0.955	0.983
[a]SMO	93.94%	0.939	0.941	0.963	0.939

[a] Previous work ref [18].

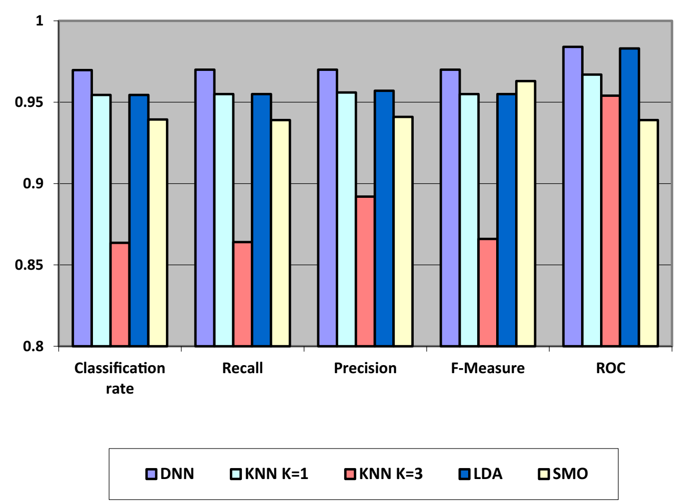


Fig. 5. Comparison graph for the performance of DNN, KNN K = 1 and 3, LDA and SMO classifiers.

- We prepared the brain MRI dataset and performed the first three steps of the methodology using MATLAB R2015a
- Weka 3.9 tool was used for performing the classifications and the evaluation of the selected classifiers.

The evaluation of the performance for the proposed methodology was measured in terms of average classification rate, average recall, average precision, average F-Measure and average area under the ROC curve (AUC) of all the four classes (normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors) and compared to the performance of other classifiers in the same terms.

As seen from Table 1 and the chart in Fig. 5, the DNN classifier gave good results combined with the DWT feature extraction tool in all the performance measures over all other classifiers.

5. Conclusion and future work

In this paper we proposed an efficient methodology which combines the discrete wavelet transform (DWT) with the Deep Neural Network (DNN) to classify the brain MRIs into Normal and 3 types of malignant brain tumors: glioblastoma, sarcoma and metastatic bronchogenic carcinoma. The new methodology architecture resemble the convolutional neural networks (CNN) architecture but requires less hardware specifications and takes a convenient time of processing for large size images (256 × 256). In addition using the DNN classifier shows high accuracy compared to traditional classifiers. The good results achieved using the DWT could be employed with the CNN in the future and compare the results.

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