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Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm

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***Abstract*—Brain tumor can be classified into two types: benign and malignant. Timely and prompt disease detection and treatment plan leads to improved quality of life and increased life expectancy in these patients. One of the most practical and important methods is to use Deep Neural Network (DNN). In this paper, a Convolutional Neural Network (CNN) has been used to detect a tumor through brain Magnetic Resonance Imaging (MRI) images. Images were first applied to the CNN. The accuracy of Softmax Fully Connected layer used to classify images obtained 98.67%. Also, the accuracy of the CNN is obtained with the Radial Basis Function (RBF) classifier 97.34% and the Decision Tree (DT) classifier, is 94.24%. In addition to the accuracy criterion, we use the benchmarks of Sensitivity, Specificity and Precision evaluate network performance. According to the results obtained from the categorizers, the Softmax classifier has the best accuracy in the CNN according to the results obtained from network accuracy on the image testing. This is a new method based on the combination of feature extraction techniques with the CNN for tumor detection from brain images. The method proposed accuracy 99.12% on the test data. Due to the importance of the diagnosis given by the physician, the accuracy of the doctors help in diagnosing the tumor and treating the patient increased.**

***Index Terms*—Brain tumor, deep neural network, Convolutional neural network, magnetic resonance imaging, feature extraction.**

I. Introduction

Brain tumors can be classified into two types: benign (non-cancerous) and malignant (cancerous). The malignant tumors can quickly spread to other tissues in the brain and lead to worsening the patient's condition [1]. When most of the cells are old or damaged, they are destroyed and replaced by new cells. if damaged and old cells are not eliminated with generating the new cells, it can cause problems. The production of additional cells often results in the formation of a mass of tissue, which refers to the growth or tumor. Brain tumor detection is very complicated and difficult due to the size, shape, location and type of tumor in the brain. Diagnosis of brain tumors in the early stages of the tumor's start is difficult because it cannot accurately measure the size and resolution of the tumor [2].

However, if the tumor is diagnosed and treated early in the tumor formation process, the chance of patient's treatment is very high. Therefore, the treatment of tumor depends on the timely diagnosis of the tumor [3]. The diagnosis is usually done by a medical examination, with computer tomography or magnetic imaging. MRI imaging is a method that provides accurate images of the brain and is one of the most common and important methods for diagnosing and evaluating the patient's brain. In the field of Medical Detection Systems (MDS), MRI images provide better results than other imaging techniques such as Computed Tomography (CT), due to their higher contrast in soft tissue in humans [4].

The proposed technique has used CNN to identify and categorize the tumor from brain images of the brain. The main difference between the main channel of the neural network with the normal neural network is that it is able to automatically and locally extract the feature from each image [5]. These types of networks consist of neurons with weights and biases that can be learned [6].

Due to the results of CNN on the dataset, in order to improve the proposed method. Machine learning algorithm is used to feature extraction. The algorithm used was the clustering algorithm applied on data set, and then the images are applied to the CNN. The results showed that the proposed method has been successful. The purpose of extracting the property before applying to the CNN is that in some images fatty masses are considered as tumors, or in some images the tumor is mistakenly considered to be fat and should have increased medical error. Extracting the attribute initially and before applying the CNN leads to improved network accuracy and increased accuracy.

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II. Related work

In [7], an automated method is used to identify and categorize MRI images. This method is based on the Super Pixel Technique and the classification of each Super Pixel. Extremely randomized trees (ERT) classifier is compared with SVM to classify each super pixel into tumor and normal. This method has two datasets, which are 19 MRI FLAIR images and BRATS 2012 dataset. The results demonstrate the good performance of this method using ERT classifier.

In [8], an automatic classification method is used to identify a tumor using a CNN with 3×3 small kernels. The method obtained simultaneously the first position for the complete, core, and enhancing regions in dice similarity, coefficient metric (0.88, 0.83, 0.77), at the BRATS Challenge 2013. In [9], Alexnet model CNN is used to simultaneously diagnose MS and normal tumors. The CNN was able to accurately classify 98.67% images correctly into three classes. In [10], a multi-stage Fuzzy C-Means (FCM) framework was proposed to segment brain tumors from MRI images.

In [11], An efficient and effective method which uses CNNs used for classification and segmentation. The proposed method, used Image-Net for extract features. The results obtained 97.5% accuracy for classification and 84% accuracy for segmentation. In [12], multiphase MRI images in tumor grading have been studied and a comparison has been made between the results of deep learning structures and base neural networks. The results show that the network performance based on the sensitivity and specificity of CNN improved by 18% compared to the neural networks.

In [13], a deep learning-based supervised method is introduced to detect synthetic aperture radar (SAR) image changes. This method provided a dataset with an appropriate data volume and diversity for training the DBN using input images and the images obtained from applying the morphological operators on them. The detection performance of this method indicates the appropriability of deep learning based algorithms for solving the change detection problems.

In paper [14], a completely automated brain tumor classification method is proposed based on DNN. The proposed networks have been designed to be used in low-grade and high glioblastoma disease images. In this paper, a new architecture of CNN is presented. The proposed a cascading architecture is proposed in which the output of a core CNN is used as an additional source of information for the next CNN.

III. Feature extraction

In machine learning and image processing, feature are created from the initial dataset. which facilitates the learning process. When the input data of an algorithm is too large, it can be converted to a smaller set of features. The process of extracting a subset from the primary features set is called feature extraction [15]. The selected features include information about the input data, so that the reduced representation of the agent can be done instead of the full initial data. One of the important application of feature extraction is in the image processing, which are used to distinguish the desired segments or the shape (features) of a digital image or video stream.

IV. Deep learning

Deep learning is one of the recent useful kinds of machine learning. In other words, learning is called deep-seated architecture. These architectures are in fact the same old nerve networks that have become DNN. These networks are data-driven and feature engineering is done automatically and we do not interfere with it, and this is precisely what makes the accuracy and excellent performance of these networks in different areas. It is in fact a deep learning of a set of nerve-based techniques that learns features automatically from our own input data [16].

A. Convolution Neural Network

The CNN are a special type of DNN whose structure is inspired by biology of cat's vision cortex [17]. The CNN has a hierarchical structure and consists of several layers. CNN also includes, input layer, output layer, convolutional layers, pooling layers, normalization layers and Fully Connected layers. CNN is different in terms of the number of layers employed, the size and number of images, as well as the type of activation functions employed. In the CNNs, the parameters are chosen experimentally and experimentally based on trial and error [18]. In other words, each CNN consists of several layers, the main layers of which are the Convolutional layer and the Sub-sampling layer which have been introduced in the following parts:

1) Convolution layer: Natural squirrels have fixed properties in the sense that statistics are part of the image exactly the same as the other parts. This means that learned features of one section of the image can also be applied to other parts, and similar features are used in all image sections. After the features are acquired, the features of Convolutional layer are used to categorize images [19] [6].

2) Sub-Sampling layer: Operations in this layer are done to reduce the size of the input image. By this layer, we receive a vector of points at the end of the CNN. The aggregation or Sub-Sampling operation is used as the mean pooling or max pooling [20].

V. Methodology

A. Dataset

The data set images used in this paper include brain MRI images of 153 patients, including normal and brain tumors patients who referred to imaging centers because of headaches After examination and diagnosis of the doctor, the collected images included brain images of 80 healthy patients Include 1321 images which has 56 images for testing data and 515 images for the train data. 73 patient tumors Include 571 images which has 170 images for test data and 1151 images for the train data. Of the total number of patients with brain tumor disease, 86 were women and 68 were men, whose age range from 8 to 66 years old. Of a total of 153 patients, 1892 images were collected, 1666 images for train data and 226 images for test images. The collected images originally had an initial size of 512×512.

B. Simulation

In few cases, some areas of fat in the pictures are mistakenly detected as tumor, or the tumors may not be seen by the physician; the most exact diagnosis is completely depended on the physicians skill. In this paper, the CNN has been used for tumor detection through brain images. There were additional margins of the images gathered from the imaging centers. These margins were cropped to prevent the noise of the images. One of the main reasons for using the feature extraction technique and combining it with the CNN is to retrieve the feature extraction of the images in order to increase the accuracy of the network. According to the results of the CNN on the initial images, in order to improve the network accuract, in this study, a new method which is a combination of Clustering algorithm for feature extraction and CNN is proposed.

C. Feature extraction method

The central clustering is a clustering method. This algorithm has a duplicate procedure that iterative, for a constant number of clusters, attempts to obtain points as cluster centers, which are in fact the same mean points belonging to each cluster. And assign each sample data to a cluster that gives the data a minimum distance to the center of that cluster. In the simple type of this method, first the cluster centers are selected randomly. The points are assign to the cluster centers according to the degree of similarity, and thus new clusters are obtained. In this paper, the first-order clustering algorithm has been used to feature extraction of the Fig. 1 shows the image obtained from applying the clustering algorithm to the image.

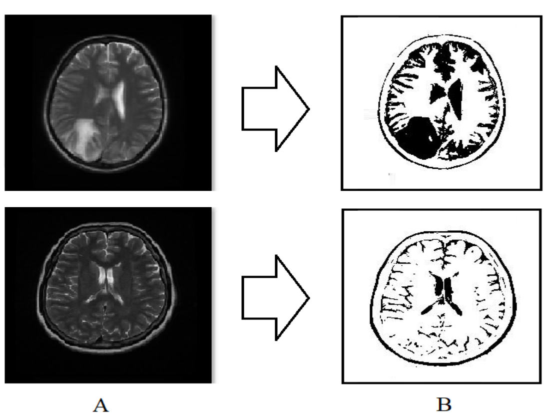

Fig. 1. Applying the clustering algorithm to the image.

D. Convolutional neural method

Initially, the images were applied to the CNN without any feature extraction methods. The size of the input images is initially 227×227. The Alexnet architect was used to identify and classify the images, which consisted of 5 Convolutional layers and 3 layers of Sub-sampling layers, Normalization layers, Normalization layers, Fully Connected layers and lastly layer the classification layer [21]. The fully connected layers have 4096 neurons. We have two classes in this layer: brain tumor patient and normal patient. The utilized CNN is shown in Fig. 2.

VI. Simulation Results and Discussion

The CNN managed to accurately categorize the images into tumor patient and normal patient tumors with precision of 98.67%. According to the results of the CNN on the initial images, in order to improve the network performance a combination of Clustering algorithm for feature extraction and CNN is used. Other classifiers such as the, Softmax Fully Connected layer classifier, RBF classifier and the DT classifier in the CNN architecture have been used to evaluate the efficiency of the proposed technique. Also, the criteria for the Accuracy, Sensitivity, Specificity, Precision have been used to verify the function of the classifier. As shown in Table I, the accuracy of the CNN is obtained by Softmax classifier used to classify images obtained 98.67%. Also, the accuracy of the CNN is obtained with the RBF classifier 97.34% and the DT classifier 94.24%. By the method proposed(combination of Clustering algorithm for feature extraction and CNN+Softmax), accuracy increased to 99.12% on the test data.

TABLE I
The results obtained from the CN on test data images with the classifier.

Methods	***Accuracy***	***Specificity***	***Sensitivity***	***Precision***	***False***
CNN+ Softmax	98.67%	94.64%	100%	98.26%	3
CNN+ RBF	97.34%	89.28%	100%	96.59%	6
CNN+ DT	94.24%	85.71%	100%	95.37%	13

According to the results obtained from the categorizers, the Softmax classifier has the best accuracy in the CNN. After reviewing the results obtained from different categorizers in the CNN, the SoftMax classification has been used in the proposed method. Initially, the dataset were given to the traditional CNN.

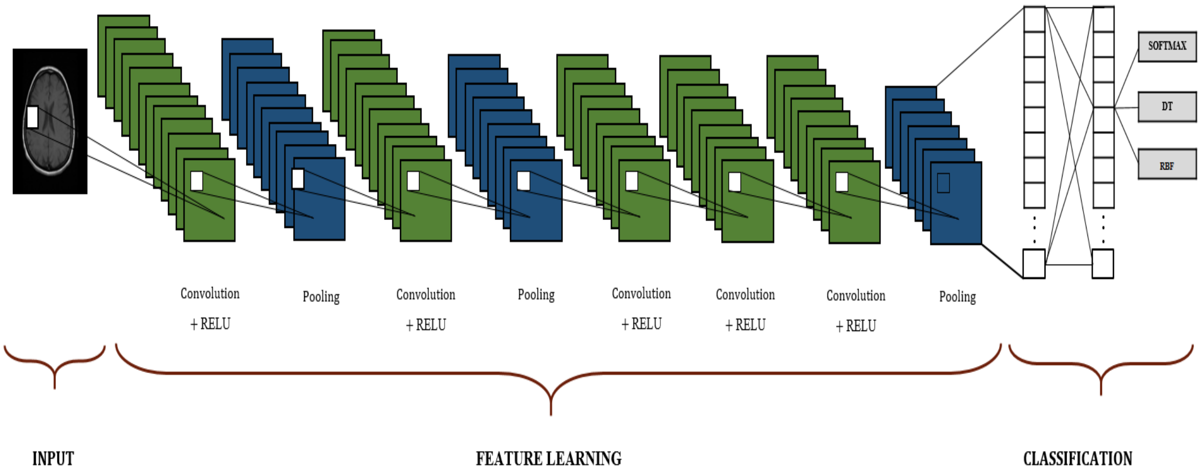

Fig. 2. Proposed CNN to gender detection using MRI images

According to the obtained results, 3 images from the total of 226 test data images were misdiagnosed and categorized as shown in the Fig. 3.

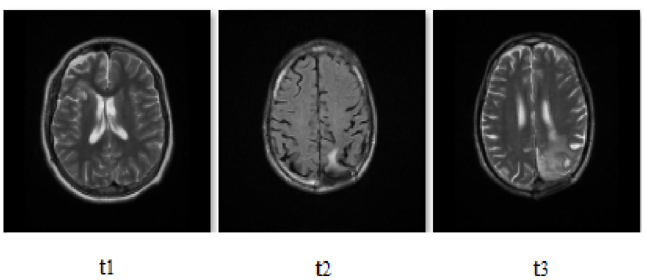

Fig. 3. Images by the CNN are mistakenly classified.

The results of CNN using the proposed method (i.e. combining the feature extraction algorithm and CNN-SoftMax) on dataset are shown in Table II. The accuracy of proposed method increased to 99.12% on the test data, which is an improvement compared to the traditional CNN.

TABLE II
THE RESULTS OF THE CNN AND PROPOSED METHOD ON THE DATA TEST IMAGES.

Methods	***Accuracy***	***Specificity***	***Sensitivity***	***Precision***	***False***
CNN+ Softmax	98.67%	94.64%	100%	98.26%	3
Proposed method	99.12%	96.42%	100%	98.83%	2

After using the proposed method, one of the misclassified images from the traditional CNN is classified correctly. The Fig. 4 of the images categorized by the proposed network is mistaken.

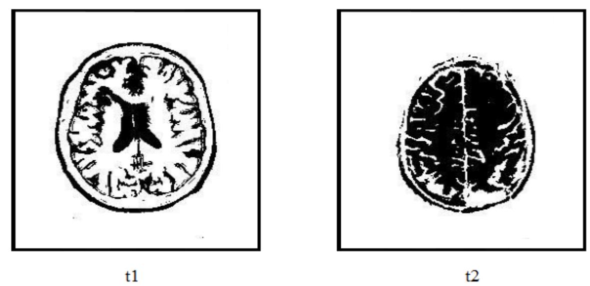

Fig. 4. Images that are wrongly categorized by the proposed method.

The diagram of the network accuracy process is also shown on the test images in Fig. 5.

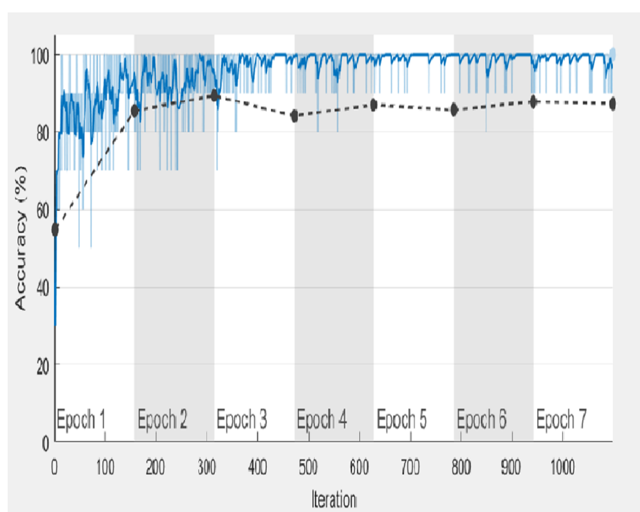

Fig. 5. Network accuracy process.

The diagram of the network loss process is also shown on the test images in Fig. 6.

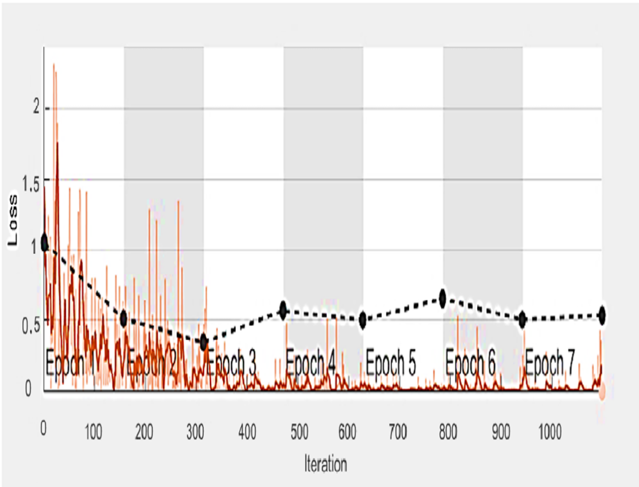

Fig. 6. Network loss process.

Conclusion

In this paper, a new method based on the combination of feature extraction algorithm and the CNN for tumor detection from brain images is presented. The CNN is capable of detecting a tumor. The CNN is very useful for selecting an auto-feature in medical images. Images collected at the centers were labeled by clinicians, then, tumor screenings were categorized into two normal and patient classes. A total of 1666 images were selected as train data and 226 images were taken as a test data. The proportion of image categorization in two classes was proportional from the ratio of patients to healthy subjects. Images were applied to the CNN after preprocessing. In order to evaluate the performance of the CNN, has been used by other classifiers such as the RBF classifier and the decision tree classifier in the CNN architecture. The accuracy of the CNN is obtained Softmax classifier 98.67% categorization. Also, the accuracy of the CNN is obtained with the RBF classifier 97.34% and the DT classifier 94.24%. In addition to the Accuracy criterion, we use the benchmarks of Sensitivity, Specificity and Precision evaluate network performance. According to the results obtained from the categorizers, the Softmax classifier has the best accuracy in the CNN. The CNN has been able to categorize accurately 98.67% images in two normal and patient classes; and from a total of 226 images, three images have been constrained by the CNN. Using the proposed method of feature extraction and applying to the CNN. The accuracy of proposed method increased to 99.12% on the test data, which is an improvement compared to the traditional CNN. Due to the importance of the diagnosis given by the physician, the accuracy of the doctors help in diagnosing the tumor and treating the patient increased high medical accuracy of the proposed method.

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