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Brain Tumor Detection Using Deep Transfer Learning Method

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Abstract
Accurate brain tumor MR images detection plays an important role in diagnosis and treatment decision making. The machine learning methods for classification only uses low-level or high-level features, to tackle the problem of classifications using some handcrafted features. Development on deep learning, transfer learning and deep convolution neural networks (CNNs) has shown great progress and has succeeded in the image classification task. Deep learning is very powerful for feature representation. In this study, deep transfer learning method for features extraction and detection is used that it does not use any handcrafted features, and needs minimal preprocessing. Transfer learning is a method of transferring information during training and testing. In this study, features extraction from images with pre-trained CNN method, namely, GoogLeNet, VGGNet and AlexNet, for tumor detection is used. The accuracy of tumor detection is 99.84%. The results show that our method, shows the best accuracy for detections tumor.

Keywords: Brain Tumor Detection, Deep Learning, Transfer Learning, Convolution Neural Networks.

1. INTRODUCTION

The brain is the most sensitive organ in our body that controls the main functions and characteristics of the human body, and according to the National Brain Tumor Association, there are about 700,000 people living with brain tumors in the United States, and that number rises to 800,000 by the end of 2021 [1]. Compared to other cancers such as breast or lung cancer, brain tumors are less common, but still the number 10 brain tumor is the leading cause of death worldwide. Brain tumors have a lasting and bad

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psychological effect on the patient,s life. A brain tumor is caused by a tissue abnormality that develops inside the brain or central spine and interrupts proper brain function. Brain tumors have been identified as benign and malignant. Benign brain tumors do not contain cancer cells and grow gradually. They do not spread and usually remain in one area of the brain, while malignant brain tumors contain cancer cells that grow rapidly and spread to other areas of the brain and spine. A Malignant tumor is life threatening and harmful. The World Health Organization (WHO) classifies brain tumors into grade 1 and 2 tumors based on brain health behavior, which are low-grade tumors and are also known as benign tumors or grade 3 and 4 tumors which are high-grade tumors and are also known as malignant tumors [1]. Brain tumors are diagnosed using several methods such as CT scan, EEG, but magnetic resonance imaging (MRI) is the most effective and widely used method. MRI uses powerful and effective magnetic fields and radio waves to produce internal images of internal organs. MRI provides more accurate information about internal organs and is therefore more effective than CT or EEG scans. In the last few years, due to artificial intelligence and deep learning, there has been significant progress in medical science, such as medical image processing, which helps physicians diagnose the disease quickly and accurately. It was time consuming. Therefore, computer-assisted technology is much needed to overcome these limitations because the Medical Field needs efficient and reliable techniques to diagnose life-threatening diseases such as cancer, which are the leading cause of global mortality for patients.

2. RELATED WORKS

Artificial intelligence and deep learning are primarily used in image processing techniques to segment, identify and classify MRI images, as well as to classify and diagnose brain tumors. So much work has been done to classify and segment the brain MRI images. Some of the international journals we have reviewed about the identification and classification of brain tumors using in-depth learning are Sheikh Bashir et al. [2] proposed a method for classifying brain tumors in which the tumor is first divided from the MRI image and then the section extracted through a pre-trained convolution neural network using a random slope descent. Mohammad Sajjad et al. [3] suggested classifying multistage tumors using the augmented method in MRI images and then adjusting them using a pre-trained CNN VNG-19 model. Carlo, Ricciardi et al., [1] proposed a method for MRI classification of pituitary adenoma tumor using polynomial logistic regression and nearest neighbor algorithms. This approach achieved 83% accuracy in polynomial logistic regression and 92% in the nearest neighbor with a 98.4% AUC curve. Khaledeh, Saed et al., [1] modified the Alex-Net CNN model to show a framework for classifying healthy and unhealthy brain MRI images, and a grading system for classifying rare brain images into low-grade and Presented above 90% Accuracy. Nyoman Abiniwanda et al. [2] trained a convulsive neural network to classify three specific brain tumor classes, meningioma, glioma, and pituitary gland, which received 98.51% training and 84.19% accuracy, respectively. Sonanda Das et al. [3] also trained a CNN model with image processing techniques to identify different types of brain tomor and achieved an average accuracy of 93.33% to 94.39%. Romeo, Valeria et al. [2] proposed a machine radiometric learning method for predicting tumor grade and node status from CT scans of primary tumor lesions and achieved the highest accuracy of 92.9 by Naive Bayes and k-nearest neighbors. Mohammad Taloo et al., [3] from the previously trained CNN ResNet34 model, used a data-driven transfer learning method to classify normal and abnormal brain MRI images with 100% accuracy. Arshia Rahman et al. [3] used three different CNN-trained models (VGG16, AlexNet, and GoogleNet) to classify brain tumors into the pituitary, glioma, and meningiomas. During this transmission learning approach, the VGG16 achieves the highest accuracy of 98.67%. Ahmet Çinar et al., [3] modified the pre-trained CNN ResNet50 model by removing the last 5 layers and adding 8 new layers instead and comparing its accuracy with other pre-trained models such as Google Net, AlexNet, ResNet50. The updated ResNet50 model showed effective results with 97.2% accuracy. The unavailability of labeled data is one of the most important barriers to the penetration of deep learning in medical health care. Because the recent development of deep learning applications in other fields has shown that the larger the data, the better the accuracy of the result. Data segmentation and data augmentation are performed using in-depth learning in the literature, and various CNN-trained models using the transfer learning method have been used to classify brain tumors. Most of the literature expresses classification efficiency using the transfer learning approach. The most commonly used pre-trained models in the literature are the VGG-16, ResNet-50 and Inception-v3, which are pre-trained with large data sets such as Image Net. And for radiology researching and testing, we have to make fine adjustments by freezing the layers to reduce the parameters if the data set is small. We also have to replace the fully connected layers according to the data set labels. Transmission training requires high processing power Specialized processors (GPUs) for fluent training, which is very expensive.

To solve the problems of machine learning methods, the deep learning has been introduced to extract the relevant information from the raw images and use it efficiently for classifications process [4, 5]. In deep learning, features are not adjusted manually instead the learning is performed from data sets with the help of general-purpose learning approach [4].In the last few years, deep learning based on Convolution Neural Network (CNN) have been used in the field of biomedical image analysis for microscopic images [6, 7] tumor detection [8], segmentation [8] skin disease [9], detection and classification [10] and quantization [11]. The CNN application works well on large data, yet on small data it fails [17]. In order to achieve accuracy and reduce the costs, the concept of transfer learning can be exploited to improve the performance of CNN method [12, 13]. The set of features is extracted from image data pre-trained deep CNN [14] diagnosis of brain tumor plays important role in effective treatment.

Manual classification of brain tumor with similar structures is a difficult task. Two types of brain tumor classification are: (i) identifying of normal or abnormal brain (ii) Classifying the different tumor types. Manual brain tumor classification is impractical and time intensive. To address, automatic classification is a solution to classify brain tumor [18]. In this research, we classify the tumor types. The CE-MRI dataset utilized in this study consists of three types of brain tumors. (Glioma, meningioma, and pituitary tumor). Compared with the binary classification (abnormal and normal), our task is more complex. Machine learning methods for classification consist of (a) preprocessing, (b) feature extraction, (c) feature selection, (d) dimension reduction, (e) classification. Problems in the feature extraction using traditional machine learning include:

a) Only low-level or high- level features are extracted.

b) On handcrafted features it depends.

In [15, 16] extraction deep features from bio-images using CNN.

Yang et al. [17] showed the capability of transfer learning with smaller dataset used GoogLeNet and AlexNet, GoogLeNet is better than AlexNet.

3. METHOD

In this study, the proposed method based on CNN is used to detect and classify the tumor type. Different low- and high-level features are extracted by CNN method of GoogLeNet, VGGNet, and ALEXNet.

3.1. Dataset

In this study, we have used a CE-MRI dataset available at (https://figshare.com /articles /brain_tumor_dataset/1512427). Here, 4 data sets are used for average accuracy and transitional learning (Archive 1 to 4) and 500 data items were used of each group.Fig.1.

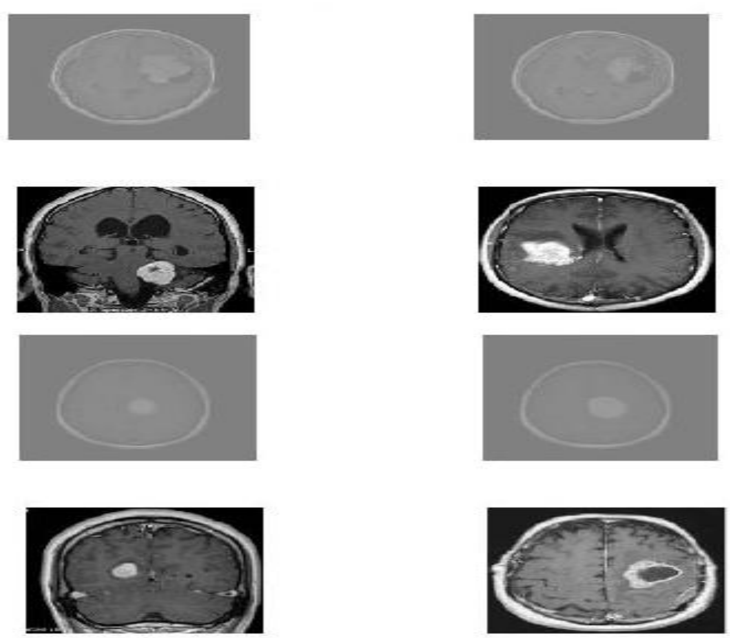

Fig. 1. The brain tumor from dataset in MATLAB software.

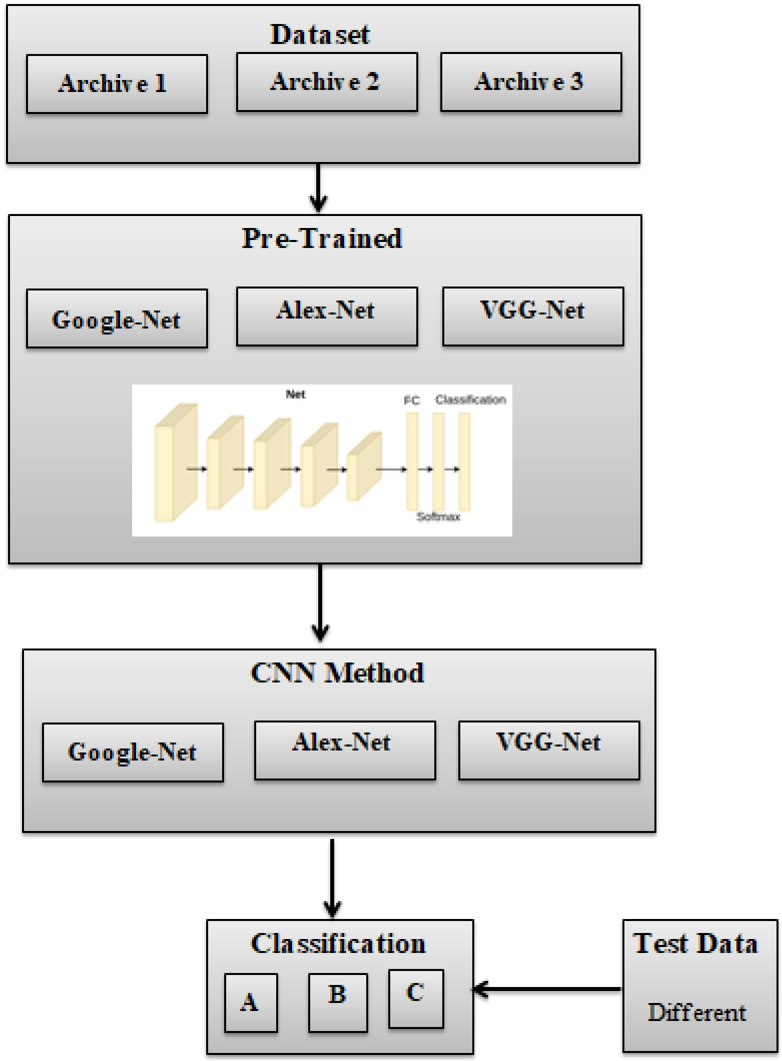

Fig. 2. block diagram of method steps.

The data was recorded during 2005-2010 from Nanfang Hospital, Guangzhou, China. The dataset contains three types of tumors (glioma, meningioma, and pituitary) shown in Fig. 1 from 233 patients with 3064 images.

3.2. Data pre-Processing and Processing

The pre-processing step is used to remove different noises.

In this study, all features are extracted without hand-crafted features. GoogLeNet, VGGNet and AlexNet are defined as a deep network with the number of learnable layers [15]. In the proposed method, transfer learning has been exploited to detect and classify the tumor. The size of the input images is resized to standard size. AlexNet, GoogleNet and VGGNet methods are used to identify and classify images. We classify the brain tumors into three types.

Block diagram of the proposed method is shown in Fig. 2.

3.3 VGG Net

The input of the cov1 layer is a fixed size 224 22 224 RGB image. The image passes through a stack of convolutional layers, where the filters are used with a very small receiving field: 3 × 3 (which is the smallest size to capture the concept of left / right, up / down, center). In one configuration, 1 × 1 convolution filters are also used, which can be seen as a linear deformation of the input channels (followed by nonlinearity). The convolution step is fixed to 1 pixel. The conical space cushion of the layer input is such that the spatial resolution is maintained after convolution, for example the screen is 3 × 3 pixels per pixel. Layers. Spatial shrinkage is done by five layers of maximum pool, which follows some turns. Layers (not all fixed layers are followed by maximum aggregation). Maximum aggregation is done in a 2 × 2 pixel window, with step 2. The three fully connected (FC) layers follow a set of convolutional layers (which have different depths in different architectures): the first two have 4,096 channels, the third classifies 1000 classes, and therefore contains 1000 channels (One channel for each class is the final layer of the soft-max layer. The configuration of fully connected layers is the same on all networks. All hidden layers are equipped with nonlinear correction (ReLU). It is also noted that none of the networks (except one network) contain local response normalization (LRN), such normalization does not improve the performance of the data set, but leads to increased memory consumption and computation time.

3.4. AlexNet

AlexNet architecture is relatively simple. There are 8 teachable layers: 5 convulsions and 3 fully connected layers. ReLU activations are used for all layers except the output layer which uses softmax activation. Local response normalization is used only after layers C1 and C2 (before activation). Maximum overlap accumulation is used after layers C1, C2 and C5. Dropout was used only after layers F1 and F2. Due to the fact that the network is located on 2 GPUs, it had to be divided into 2 parts that are only partially connected. Note that layers C2, C4, and C5 are only received as inputs of the previous layers on the same GPU. Communication between GPUs occurred only at layer C3 as well as F1, F2 and the output layer. The network was trained using a random slope with acceleration and drop in learning. In addition, during training, whenever the validation error speed is stopped, the amount of manual learning is reduced by a factor of 10.

3.5. Google Net

The input image to the convolution neural network must be 225×225 in size.

3×3 reduce, and ,5×5 reduce, stand for the number of 1×1filters in the reduction layer used before the 3×3 and 5×5 convolutions.

Figure 2 shows all the steps of the proposed metho.. Here, we use one data set, such as Archive 1, for training and another for testing .This mode becomes 6 steps, and we performed all these steps for three methods AlexNET, GoogleNet and VGGNet.A total of 18 modes were performed for processing and all results are reported.

4. RESULTS

Three data sets were collected and entered into MATLAB software. And reduced possible initial noise and images were resized to 227*227 for processing and inserted to network.

The results of all steps are reported.

Table 1 shows the transfer learning results of 6 modes of training and testing with different data with the AlexNet network.

Table 2 shows the transfer learning results of 6 modes of training and testing with different data with the GoogleNet network.

Table 3 shows the transfer learning results of 6 modes of training and testing with different data with the VGGNet network.

Table 1 presents the results for the AlexNet deep network in the first part, which is from 1 to 2 this means that the first database was used for training and the second database was used for testing. And the results

Table 1. Results of AlexNet.

Transfer learning Train Data Test Data	Network	ccuracy %	Sensitivity %
1→2	AlexNet	96.64	95.48
1→3	AlexNet	97.32	97.16
2→1	AlexNet	98.48	96.28
2→3	AlexNet	96.32	95.84
3→1	**AlexNet**	**99.74**	**99.54**
3→2	AlexNet	95.64	94.54

Table 2. Results of Google Net.

Transfer learning Train Data Test Data	Network	ccuracy %	Sensitivity %
1→2	GoogleNet	97.72	96.86
1→3	GoogleNet	98.48	98.24
2→1	**GoogleNet**	**99.84**	**99.64**
2→3	GoogleNet	97.36	94.64
3→1	GoogleNet	98.98	97.76
3→2	GoogleNet	99.54	98.68

Table 3. Results of VGGNet.

Transfer learning Train Data Test Data	Network	ccuracy %	Sensitivity %
1→2	VGGNet	95.68	94.54
1→3	VGGNet	96.74	96.12
2→1	VGGNet	97.86	97.14
2→3	**VGGNet**	**98.92**	**98.46**
3→1	VGGNet	96.82	96.56
3→2	VGGNet	93.68	92.52

are reported and the same thing is done for all three data sets with different scenarios and the results of each step are reported in the table. The same is done for VGG and Google networks and the results are reported in Tables 2 and 3.

5. CONCLUSIONS

Here we have reviewed 6 different modes for each network and announced the results. We chose the best result from 18 performed modes, as you can see in Tables 1, 2 and 3. The best classification result is obtained in Alex network, and it has 99.84% accuracy. As you can see, the proposed method is more accurate than other methods and has acceptable results.

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