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Detection of Brain Tumors using Neural Networks

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Abstract: The brain tumors are most common and aggressive disease, leading to very short life expectancy rate. Thus, treatment at initial stage is a key stage to improve the quality life of patients. There are image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) , ultrasound image which are used to evaluate the tumors in brain, lung and liver. MRI images are used to diagnose tumors in the brain. There are few limitations for the manual classification of tumors. Hence automatic classification scheme is introduced to prevent the death rate of human. In this work, automatic classification is done through MR images using neural networks. In our proposing system, we are implementing new algorithm for detection of tumors with more accuracy. Thus, the automatic tumor detection will more accurate.

1. Introduction

The brain is a three-pound organ which controls all functions of the body, and also helps to interpret information from the outside world. Brain consists of cerebrum, cerebellum, and brainstem. All functions of our body are controlled by the brain, since damage to that one organ results in extreme harmful changes in our body.

Brain is a large composition of different cells, when these cells are computed in their DNA, they also tend to grow and divide at increased rates. These abnormal cells results in the formation of tumor.

Tumors start from the brain itself or in tissues such as meninges, nerves or pituitary gland. Tumors are of two types, they are primary brain tumors and secondary brain tumors. Primary brain tumors originate from brain itself and form a clot like structure in brain, it exists for certain period. When that clot spreads to the different parts of the body it leads to cancer, this type of tumor is named as is called secondary brain tumor.

There are different types of tumors based on the cells involved in the abnormal growth. They are gliomas, meningiomas, schwannomas, Pituitary adenomas, Medulloblastomas, Germ cell tumour's, Craniopharyngiomas etc. There is another form of cancer that begins somewhere in the body and spreads to the brain. These types of tumors are most common in adults. Breast cancer, Kidney cancer, Lung cancer are

few different forms of cancer that originate from other parts of body. So it is important to diagnose tumor in brain itself, before turning to cancer and cause severe damage. Detection of tumor is important in its early stage itself. There are various stages of during diagnosis of tumors, they are physical exam, laboratory tests, image tests and finally doctors conclude through biopsy.

Although there is a different process to diagnose cancer, final decision is made by doctor.it is difficult to identify the tumor based on this procedure. That is, there should a technique to give the maximum percentage of chances of having in tumor. There are various techniques already implemented that can easily distinguish the tumors in brain from MRI images using various machine learning algorithms such as svm, neural network etc. In this article, detection of tumors accuracy is done through Convolutional neural network.

2. Datasets

The dataset is from Figshare brain tumor dataset, https://doi.org/10.6084/m9.figshare.1512427.v5, It is a combination of 3064 brain MRI images from 233 patients, who are diagnosed with three brain tumors (meningioma, glioma(fig2) and pituitary tumors). They contain about 1426 brain MRI images with glioma(fig2) 708 images for meningioma and 930 images related to cases of pituitary tumor. The images contain the average of six slices of brain .These are the images of the original tumor patients who are diagnosed based on their conditions. The symptoms of occurance of in patients are relevant to each other.

These images are compared with the normal human brain and based on the diagnosis it was conformed of tumors. As the dataset is small and all the mri images are clear, the occurance of errors while implementing the algorithm is negligible. These images are well trained by the classifiers. Tumor images are classified after the training of the parameter classifiers. The classifier recognizes images of both normal brain (fig1) and abnormal brain. They can also identify exact location and size of tumor in brain.

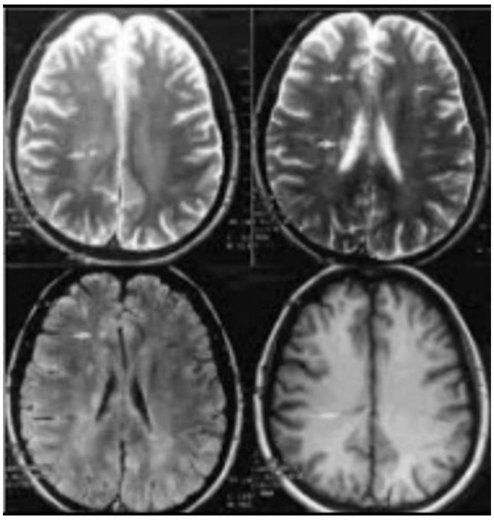

Fig.1 NORMAL BRAIN

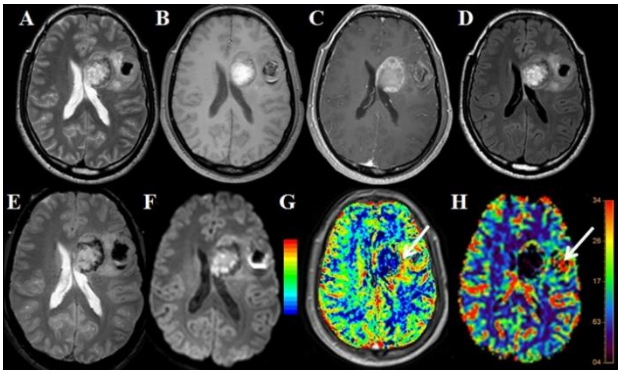

fig.2 GLIOMA

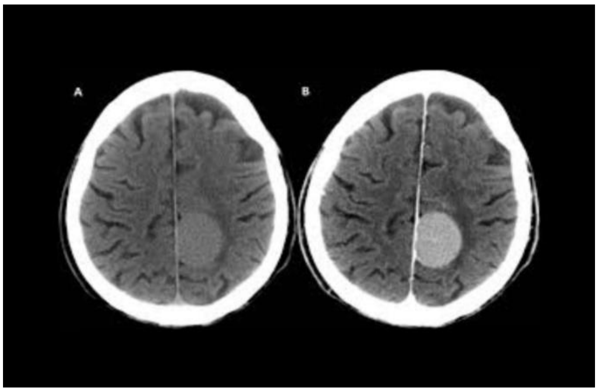

Fig.3 MENINGIOMA

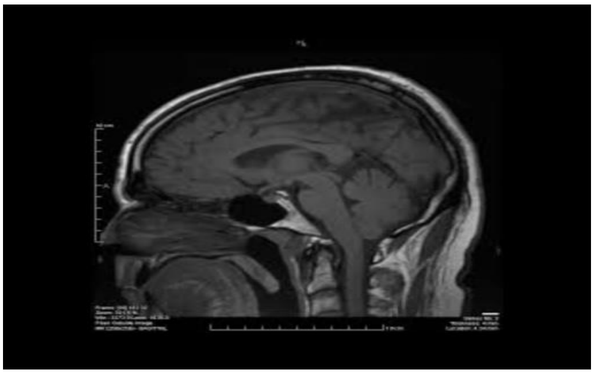

fig.4 PITUTORY TUMOR

2.1. Pre-processing and normalization

Pre-processing technique is helpful to improve the intensity of our MR images. Process of Pre-processing of an image is improves the image data from unwilling distortions and also enhances few image features important for further processing. Image normalize process changes the image pixel intensity value. We also reshape images to the lower and equal value. Images are normalized into (255 * 255) pixel sizes. Process of re-scaling is done in the range between [0,1]. We only consider one slice of brain in each MR image.

2.2. Data augmentation technique

We usually train larger datasets to reduce the overfitting in any machine learning model. In this technique we create a fake data and add it to the original dataset. this process is known as data augmentation. As we are dealing with the small dataset around 3024 images, we need data augmentation so that data can generalized. In our proposed method, images are manipulated by applying random changes like changing their pixel, scaling sizes and fluctuating their rotation, mirroring tumor images etc. Our dataset initially consists of 3024 images .We also apply data augmentation process to increase the fake data. Then 80% of total images are used for train and remaining 20% images are used for testing.

2.3 Convolutional neural network

We describe several structures, parameters and convolutional 2D layers while constructing a CNN model. Deep learning algorithms are one of the type that is included in machine learning. Deep learning makes concepts simple and easy way. It is very easy to create, characterize and recongnize the concepts in deep learning. Multilayer models are also enabled to learn large data representation. CNN model is more efficient to handle large dataset with high complexity.

CNN model includes feed-forward and feed-backward stages. Feed-forward stage helps to give the desired output based on our input whereas feed-backward re-evaluates the whole feed-forward corrects errors in its initial stage. These both happen simultaneously one after other. Then it constructs convolutional layers to divide the datasets in the form of kernals. Padding helps to filter the 2-Dconvolutional layers. Although there are two different types of pooling same-pooling is commonly used. In this paper we are using same-padding.

2.4 Activation function:

An activation function helps to reduce the complexity in the model while training an image dataset. Here we used Rectified linear unit (ReLU) and softmax as activation function. ReLU function is compared to the present linear functions and make negative values to zero to decrease the complexity.

2.5. Pooling Process

After the process of convolutional layers, we used pooling layers in the model. Pooling layer helps to reduce the total number of parameters used in the filtering process and also helpful in decreasing the size of mapping. Pooling layers of two types max-pooling and min-pooling. Here we used max-pooling of size (2x2). In addition to it we also apply strides of value ‘2‘to shift the pixels.

2.6. Dropout

A typical problem is arised when a generated algorithm performs well in both training and entering new entries in a dataset. So to solve this issue several methods of regularization for deep learning are proposed. Dropout automatically deletes its values to console the convolutional layers.in our model we used dropout after every max-pooling layer. There are four dropout layers for four convolutional layers. At the end of the designing of model we used one flatten layer so that the dataset attains few new values.

2.7. Loss function of the dataset

It is important to select proper loss function while designing any deep neural network. The loss should be minimized either in testing or training the algorithm.so we are using Categorical cross-entropy function (H) which is suitable for this network structure. It minimizes the average loss of epochs constantly.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 64)	1664
max_pooling2d (MaxPooling2D)	(None, 64, 64, 64)	0
dropout (Dropout)	(None, 64, 64, 64)	0
conv2d_1 (Conv2D)	(None, 64, 64, 16)	25616
max_pooling2d_1 (MaxPooling2	(None, 32, 32, 16)	0
dropout_1 (Dropout)	(None, 32, 32, 16)	0
conv2d_2 (Conv2D)	(None, 32, 32, 84)	5460
max_pooling2d_2 (MaxPooling2	(None, 16, 16, 84)	0

dropout_2 (Dropout)	(None, 16, 16, 84)	0
conv2d_3 (Conv2D)	(None, 16, 16, 96)	290400
max_pooling2d_3 (MaxPooling2	(None, 8, 8, 96)	0
dropout_3 (Dropout)	(None, 8, 8, 96)	0
flatten (Flatten)	(None, 6144)	0
dense (Dense)	(None, 120)	737400
dense_1 (Dense)	(None, 64)	7744
dropout_4 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 4)	260

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Total params: 1,068,544

Trainable params: 1,068,544

Non-trainable params: 0

2.8 Datasets Testing

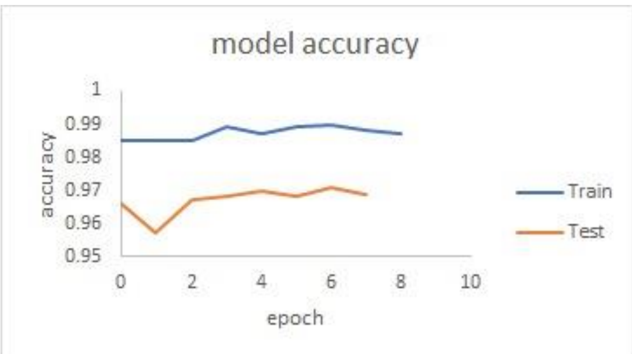
After training the dataset through nadam optimizer Testing mechanism is done many methods. Nadam optimizer updates momentum's parameter steps and precision steps are taken more into consideration before computing the gradient direction. Here we use evaluation test method and compare with test-sets and then we can get to know accuracy of correctly finding images. By doing this we got 97% of accuracy and 0.17% as loss percentage.

3. Results and discussion

Classification of algorithm's performance is evaluated in different ways. We are using matplotlib library to conclude the average performance of both testing and training. We also used the confusion matrix to check the information of the dataset, the performance is assessed from different aspects. By finding accuracy, we can also analyze precision and also get through know about true positives and true negatives. We can also define False positives and False negatives to count the total cases which detects the classifer's condition whether it is absent or present. These all values can be easily derived from confusion matrix. Here, we had an average accuracy for detecting the images is about 97% and also has less loss of about 0.17%.Hence, we can conclude that the accuracy for tumor detection through MR images is about 97%.

RESULTS:

[0.174737349152565,0.9700000286102295]



4. Conclusion

A new convolutional neural network model has been introduced for detection process of brain tumors using MR images. Our new method has been upgraded with accuracy, image classification of three-type brain tumors. Our proposed method also decreases the time required to analyze biopsy. So that tumors can be easily identified at their early stages and their treatment can done in proper time. Our proposed method can reduce the manual work of doctors. It can not only identify the tumor but also able to give detailed analysis of occurrence of tumor in brain. Our proposed method is compared to other learning algorithms and gave best results compared to other algorithms. Although, we had best performance and high accuracy, this algorithm should work on all types of tumors and with large datasets as possible. So we plan to continue our further work on large datasets with more different types of tumors.

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