Brain Tumor Segmentation based on MRI images using CNN

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Abstract

A Brain tumor is an abnormal growth of cells inside the skull. A malignant brain tumour is a fast-growing cancer that spreads to other areas of the brain and spine. Magnetic resonance imaging (MRI) is a popular method for detecting brain tumors. The improvement of machine and deep learning techniques can help doctors in tumor diagnostics without invasive measures. Moreover, a manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties. One of the deep learning algorithms that has achieved substantial results in image segmentation and classification is the convolutional neural network (CNN). In this project we focused on three tumor types: Glioma, Meningioma, Pituitary and classify them using CNN model. Learning eventually obtained accuracy of 0.9779 and 0.9305 for training and testing, respectively. It could be interpreted as a good results despite slight overfitting.

I. Introduction

Brain tumors can be classified as benign and malign. Some of the common brain tumors are gliomas, meningiomas, and pituitary tumors, where meningiomas are being classified as benign, and gliomas as malignant, pituitary even if benign, can cause some harm. Therefore, it is very important to precisely and correctly identify and recognize tumor types for further clinical diagnostic process and for later effective treatment of patients. The widely used method for detecting brain tumors is magnetic resonance imaging (MRI). However there takes a place of human subjectivity. In order to obtain the full diagnostics of the tumor, the tissue should be examined to identify whether it is benign or malign using biopsy. A biopsy of a brain tumor is usually not done until the brain surgery. From here in order to avoid subjectivity and surgical intervention, arises a need to develop and obtain an effective tool for precise diagnostics for tumor classification using MRI images.

The development of AI allows nowadays to develop new effective models that can be applied in medicine. Deep convolutional neural networks (CNNs) have shown record performance in solving a variety of computer vision tasks such as object recognition, human activity identification, face based person identification. These techniques have also been widely used in the medical image analysis field for lesion segmentation, anatomical segmentation, and classification.

CNNs learn the relationships among the pixels of input images by extracting features using convolution and pooling operations. The features detected at each layer using learnt kernels vary regarding their complexity, with the first layer extracting simple features, such as edges or lines, and the later layers extracting more complex features. The advantages of using CNN models include: the weight-sharing mechanism helps to deal with high dimensional data, such as 2D images or 3D data, including as videos and volumetric images, moreover, slight shift invariances can be achieved using pooling layer.

II. Methods

A. Image Database

The database contains 100, 115, 74 and 106 images of correspondingly glioma, meningioma, petuitary, and no tumor in testing file, and 826 (glioma), 822(meningioma), 827(petuitary), 395 (no tumor) in training file.

B. CNN

The Convolutional Neural Network is utilized to predict the types of brain tumor [Figure 1]. The reason is that CNN provides with better zooming image pixels in comparison with other methods. Particularly, in the process the pooling layers of certain small areas and connected components could be considered. Subsequently, chosen details is utilized to classify the types of brain tumor. In addition, Keras library is used to implement the algorithm of CNN.

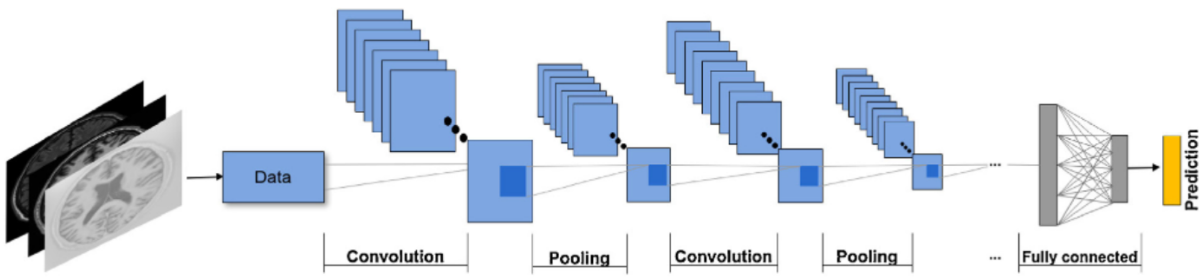

Figure 1

C. Image pre-processing and implementation

The initial image size is 512x512, but since the resolution of neural network is limited the image representation is resized to 128X128 pixels The algorithm consists of 2 hidden, 1 input and 1 output layers. In each layer, there exists 2D convolution layer, which to produce tensor of outputs. The dimensionalities of the output space were 64, 64, 1024, 4, consistently. Padding is set to 'same' in each layer and the activation function to use is assigned to 'relu' except the last layer, which is 'softmax'. In the last 2 layers dence() function is used to calculate this "output = activation(dot(input, kernel) + bias)" expression. The regularization is implemented by dropout function, where randomly selected neurons are ignored during the training process. Also, the network is flatten out after second layer by keras's flatten() function. Finally, the Adam algorithm,which is SGD based on adaptive estimation of first order and second order moments, is used to optimize.

D. Comparison with other algorithms

Additionally, to compare the CNN with other machine learning algorithms, Decision Tree Classifier and Random Forest Classifier were also fit the training data and obtained models predicted the labels of test data.

III. Results and Discussion

By using CNN, the final accuracy for train and validation data are 0.9779 and 0.9305, respectively. The difference of accuracy between the first and the last epoch was significant. The values of difference are 0.4008 and 0.3282 for train and validation samples respectively. In addition, from the Figure 2 it is seen that there is a considerable change in the values of loss. For instance, for the initial epoch of train data, it displays 1.1193, however, for the last epoch 0.0699. Finally, the accuracy of test sample was 0.89. In accordance with Graph 2, the degree of overfitting is approximately 8 percent. According to results, it can be concluded that during the training process the model learn and predict the given data sample relatively good. The data is also fitted by other machine learning algorithms such as Decision Tree, Random Forest and SVC. The accuracy value for Decision Tree is 0.68, for Random Forest 0.86 and for SVC 0.81. By analyzing results, the CNN model predicts the types of brain tumor slightly better than others.

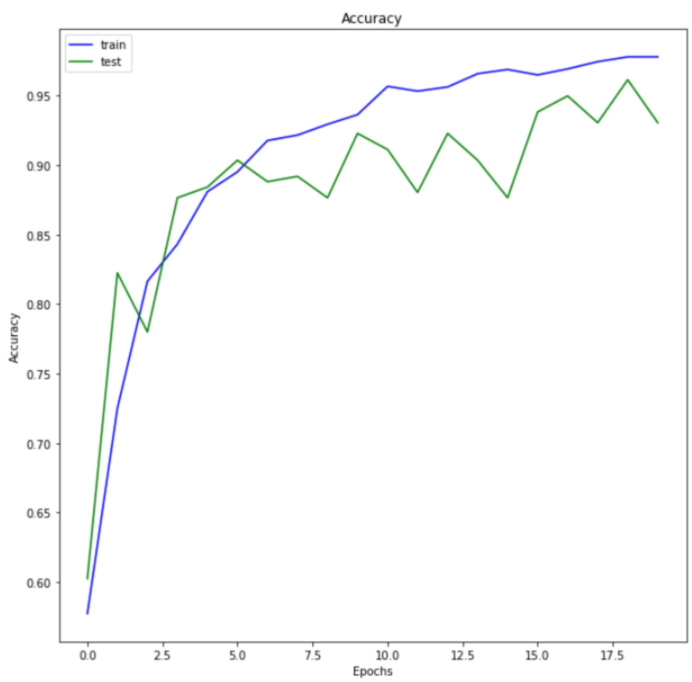

Figure 2

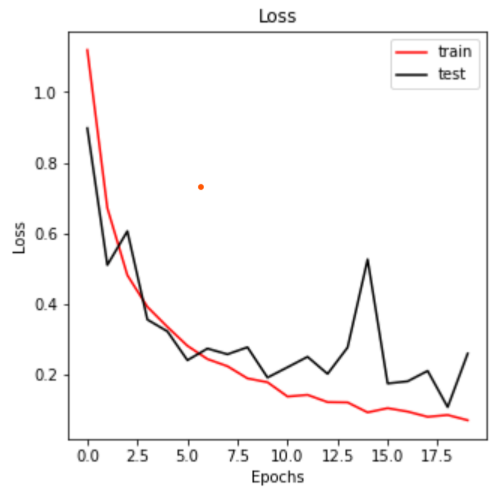

Figure 3

IV. Conclusion

In this project the Convolutional Neural Network model was used to classify different types of brain tumors. Learning eventually obtained accuracy of 0.9779 and 0.9305 for training and testing. Which could be interpreted as a good results despite slight overfitting. Moreover, CNN model was compared with other models, namely, with Decision Tree, Random Forest, and Support Vector Machine. Random forest obtained accuracy of 86%, Decision tree - 68%, SVM - 81%. However, the dimensionality of data needed to be adjusted from 3D to 2D in these cases. As we can see, CNN performs considerably effective for classification of images into multiple classes. Moreover, comparing the obtained testing accuracy of 93% with other results in literature, namely results by IEEE where also 93% accuracy was achieved, it is quite an effective outcome. However, there were some limitations in terms of that the optimal number of hidden layers was obtained experimentally without basing on some scientific background, also there was a slight overfitting with the model predicting by 8-10% more accurately on training data than on testing one. Further work can be done here to find a more effective model by making a hybrid one with other algorithms.

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APPENDIX A
CONTRIBUTION

Each member of project contributed equally: each made a version of cnn model, and then we collectively adjusted it to obtain the optimal solution, then each of us took one of three models (tree, forest, svm) to compare with cnn, and the report was divided between three of us.