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Detection of Brain Tumor

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Abstract

Brain tumor is cancerous or non-cancerous growth of abnormal cells within the brain. Brain tumor detection could be a very challenging and tedious job. So as to detect the brain tumor within the patients MRI images are used. This project aims at detecting brain tumor using one of the deep learning algorithm namely convolutional neural network. The implementation ends up in efficient performance in detecting the brain tumor and help the doctors to produce the proper diagnosis to the patients at the sooner stages.

Keywords: *Brain tumor, Brain tumor detection, convolutional neural network, keras, magnetic resonance imaging.*

1. Introduction

Brain tumor affect the humans badly, due to the abnormal growth of the cells within the brain. It can disrupt proper brain function and might cause threat to life. This can affect people of any age group. A brain tumor is classified into different types; these tumors can either be Malignant (cancerous) or Benign (non-cancerous).

A malignant tumor is a fast-growing cancer that spreads to other areas of the brain and spine. A benign tumor is a mass of cells (tumor) that lacks the power to attack neighboring tissue. However, they can even be large sometimes. When removed, benign tumors usually don’ t grow back, whereas malignant tumors sometimes do. Unlike most benign tumors elsewhere within the body, benign brain tumors can be life threatening. Benign tumors generally have a slower growth rate than malignant tumors and the tumor cells are usually more differentiated .They are typically surrounded by an outer surface or remain with the epithelium. Common examples of benign tumors include moles and uterine fibroids.

Hence, early detection of brain tumors can play efficient role in diagnosing the patient with the right treatment and might assure the patients survival rate. But the manual detection of the brain tumor is a tedious job and therefore the time consumption rate is additionally high. This paper, proposes an efficient way of detecting the brain tumor which makes the detection easy and less tedious. The rest of this paper has been structured as follows: Literature on different brain tumor classification methods is reviewed in section 2. Introduction to CNN is given is section 3. Proposed methodology is explained in section 4. Results of implementation of the proposed model are discussed in Section 5. Finally, conclusions are presented in Section 6.

2. Literature Survey

Before the arrival of deep learning techniques, the techniques used for computer vision was feature extraction followed by classification. Features were extracted using SIFT, SURF, local binary patterns, histogram of gradients. These features were classified using machine learning algorithms. The machine learning algorithms used were K-means clustering [8], Principal Component Analysis (PCA), random forest and Support Vector Machines (SVM) [12].

The feature generation step is eliminated by using deep learning algorithms which does automatic feature extraction followed by classification. Much research work has been done which motivated us in using one of the deep learning algorithms called CNN for implementation [6], [9]. [3] focuses on the employment of tensorflow for the detection of brain cancer using MRI. CNN is implemented using tensorflow. [5]

This paper provides a short overview of the multiple layers of convolutional neural networks algorithm presented within the literature containing comparative study of various techniques used for

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various stages. [1] proposes new methods of analyzing MRI images of the patients. The pre-processing is dealt by Gaussian which is linear filter. Then feature extraction for the pictures is done by GLCM features. Finally, classification is applied through an algorithm convolutional neural networks which will identify the tumor regions. [4] proposes different classification algorithms are used for diagnosis. Three separate databases of the disease are used for the prediction of the disease. [5] proposes the convolutional neural networks are widely used for image classification tasks. A less complex convolutional neural network model is employed which has the accuracy of 99.68%. MRI scans of axial, coronal and sagittal planes are employed in both training and testing sets.

3. Introduction To CNN

CNN are a set of algorithms which are modeled based on how the human brain functions. They are designed to recognize patterns. As in a human brain a CNN is constituted of basic units called convolutional filters or kernels.

The kernels in CNN work kind of like the neurons within the brain they accept an input and fire an output. The CNN is made up of activation functions to convert linear output to nonlinear. The activation functions include ReLU, tanh, sigmoid or leaky ReLU. CNNs are called so as they use a layer called convolutional layer where a special function called convolution is administered. These layers consist ofa set of filters which can be assumed as 2-D matrices with numbers.

An input image is convolved with a filter to produce an output image. During convolution the filter is overlaid on top of the image at a specific location first, then an element-wise-multiplication is performed between the values within the filter and the corresponding values within the image. These values are summed up which supplies the value of the destination pixel.

To get an output image of the identical size as the input image we use Padding. Padding is that process of adding zeros around a picture so that it is convenient to overlay the filter in additional places. This can be called same padding and not using any padding is termed valid padding. Conv layers produce similar values as output for neighboring pixels as they have similar values. This causes redundancy in values. Pooling layers are implemented to overcome this. They reduce the input image size by pooling the values together by either maximum pooling or average pooling.

The matrix of values is flattened into a vector and fed into a fully connected layer. With the fully connected layers we combine the features to create a model. Lastly an activation function like SoftMax or sigmoid is used to classify the output.

4. Methodology

The Dataset

The necessary brain MRI images used as dataset for this research were obtained from Kaggle [12] which is an online community owned by Google, Inc. used by various data scientists and machine learners. The MRI scans are available in the JPG format which is very convenient. The dataset has a total of 253 images labelled into two classes. The first class contains 155 MRI images affected with tumor and the second class containing 98 images which are free of tumor (healthy brain images). The figure 1 shows two MRI images with and without tumor respectively

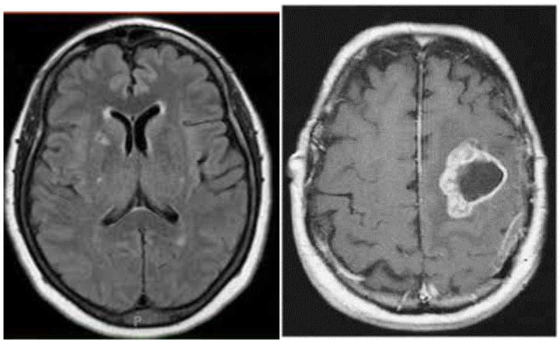

Figure 1: Brain MRI image with and without tumor.

The proposed CNN model

For accurate brain MRI classification, a deep convolutional neural network is proposed in this research. The architecture of the proposed model is shown in figure 2. This network has nine layers consisting three convolutional layers, three max pooling layers, one flattening layer and two dense layers.

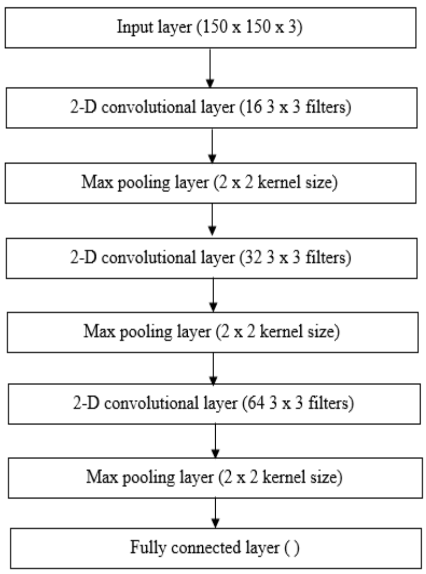

Figure 2: Proposed Convolutional Neural Network Architecture

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The input image is resized to 150 X 150 pixels and each image having 3 color channels. The input data is fed to the CNN model. The first convolution layer is made of 16, 2-D convolutional filters of size (3 x 3). It then applies an activation function Rectified Linear Unit (ReLU) for non-linear computations. The output from this layer is down sampled by max-pooling with a kernel size (2 x 2). The output from here is further subjected to two more convolution layers with 32(3 x 3) filters and 64(3 x 3) filters respectively. The two convolution layers use ReLU activation function. The working of ReLU for input x is mentioned in equation (1).

$$f(x) = \max(0, x) \qquad (1)$$

The output from the second convolutional layer is subjected to max pooling with kernel size (2 x 2) and this output passes through the third convolutional layer and again goes through max pooling layer with kernel size (2 x 2). The result from this layer is flattened and passed through a dense layer with 64 units and ReLU activation function and through another dense layer with a single unit and sigmoid activation function. The working of sigmoid function for input x is mentioned in equation (2).

$$f(x) = 1 / 1 + \exp(-x) \qquad (2)$$

Implementation

The implementation of the proposed model was done using Keras on TensorFlow and other python libraries such as Numpy, matPlotlib. Once the model was built and compiled, it was trained using training images with a batch size of 32 over 50 epochs for each batch. The learning rate was fixed to 0.001, optimizer used was RMSprop to reduce oscillations and the loss function used was binary cross entropy. Since the dataset used for this research is not very large it is assumed that 50 epochs per batch is sufficient. A callback function is used to monitor the testing and training accuracy and stop the training process once the required accuracy was obtained. This is a very efficient method as there are two advantages including prevention of over fitting and training until required accuracy is reached.

5. Experimental Results

The data considered here is a set of MRI images which are used in the training and testing sets. The test set has 54 MRI images and the training set consists of 192 images. The model was found to work well with the layers implemented and we were able to obtain an average training accuracy of 95% validation accuracy of 90%, training loss of 25% and validation loss of about 33%. Also, the result of applying the proposed method is shown in fig 3.

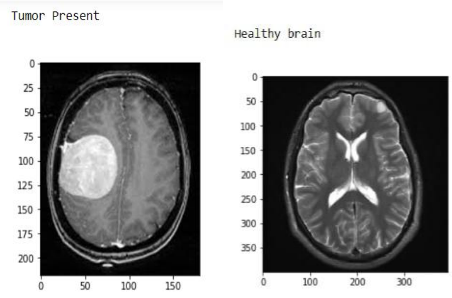

Figure 3: Final output

6. Conclusion

Detection of brain tumor is essential as it leads to saving life of people. The process of brain tumor detection could be automated and the result could serve as the second opinion and the task of radiologists could be less burdened especially in countries having shortage of radiologists. The paper proposed a deep learning approach called CNN for detection of tumor in a given brain MRI image. The results of implementation are quite satisfactory as the accuracy obtained is above 90%.

References

[1] Harshini Badisa, Madhavi Polireddy, Aslam Mohammed," Cnn based brain tumor detection, vol 8, April 2019

[2] Navoneel Chakraborty, " Brain MRI Images for Brain Tumor Detection, on Kaggle updated in Apr 2019.

[3] Aaswad Sawant, Mayur Bhandari, RaviKumar Yadav, Rohan Yele, Mrs. Sneha Bendale" Brain cancer detection from MRI: A machine learning

[4] approach (Tensorflow), vol.05, 04, April 2018

[5] Pahulpreet Singh Kohli, Shriya Arora," Application of machine learning in disease predction" -2018

[6] Ali Fadhil Yaseen, " Survey on the layers of convolutional neural networks" , vol.7, 12, December 2018, pg. 191-196

[7] Narmada M. Balasooriya, Ruwan D. Nawarathna," Sophisticated convolutional neural network model for brain tumor classification, 2017

[8] Sergio Pereira, Adriano Pinto, Victor Alves, Carlos A. Silva," Brain tumor segmentation using convolutional neural networks in MRI images, vol. 35, May 2016

[9] K. D. Kharat, V. J. Pawar, and S. R. Pardeshi, " Feature extraction and selection from mri images for the brain tumor classification," in 2016 International Conference on Communication and Electronics Systems (ICCES), Oct 2016, pp. 1– 5.

May-June 2020
ISSN: 0193-4120 Page No. 4856-4859

[10] R. Lang, L. Zhao, and K. Jia, " Brain tumor image segmentation based on convolution neural network," in 2016 9th International Congress on Image and Signal Processing, Biomedical Engineering and Informatics (CISP-BMEI), Oct 2016, pp. 1402– 1406.

[11] N. Sauwen, D. M. Sima, M. Acou, E. Achten, F. Maes, U. Himmelreich, and S. V. Huffel, " A semi-automated segmentation framework for MRI based brain tumor segmentation using regularized nonnegative matrix factorization," in 2016 12th International Conference on Signal-Image Technology Internet-Based Systems (SITIS), Nov 2016, pp. 88– 95.

[12] [11] M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, " Design and implementation of a computer-aided diagnosis system for brain tumor classification," in 2016 28th International Conference on Microelectronics (ICM), Dec 2016, pp. 73– 76.

[13] [12] L. Zhao and K. Jia, " Deep feature learning with discrimination mechanism for brain tumor segmentation and diagnosis," in 2015 International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), Sept 2015, pp. 306– 309.