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Efficient Brain Tumor Segmentation with Multi scale Two-Pathway-Group Convolutional Neural Networks

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ABSTRACT: Manual segmentation of the brain tumors for cancer diagnosis from MRI images is a difficult , tedious and time consuming task.The accuracy and the robustness of brain tumor segmentation, therefore, are crucial for the diagnosis, treatment planning, and treatment outcome evaluation. Mostly, the automatic brain tumor segmentation methods use hand designed features. Similarly, traditional methods of Deep learning such as Convolution Neural Networks require a large amount of annotated data to learn from, which is often difficult to obtain in the medical domain. Here we describe a new model Two-Pathway-Group CNN architecture for brain tumor segmentation, which exploits local features and global contextual features simultaneously. This model enforces equivariance in the Two-Pathway CNN model to reduce instabilities and over fitting parameter sharing. Finally,we embed the cascade architecture into Two-Pathway- Group CNN in which the output of a basic CNN is treated as an additional source and concatenated at the last layer.

KEYWORDS: Data set, Data preprocessing, Deep learning, Convolutional Neural Network, Tumour detection.

I. INTRODUCTION

Brain tumor identification is really challenging task in early stages of life. But now it became advanced with deep-learning. Now a day's issue of brain tumor automatic identification is of great interest. In Order to detect the brain tumor of a patient we consider the data of patients like MRI images of a patient's brain. Here our problem is to identify whether tumor is present in patients brain or not. It is very important to detect the tumors at starting level for a healthy life of a patient. There are many literatures on detecting these kinds of brain tumors and improving the detection accuracies. In this paper, we estimate the brain tumor severity using Convolutional Neural Network algorithm which gives us accurate results.

In figure 1 The different types of brain tumours are outlined below:

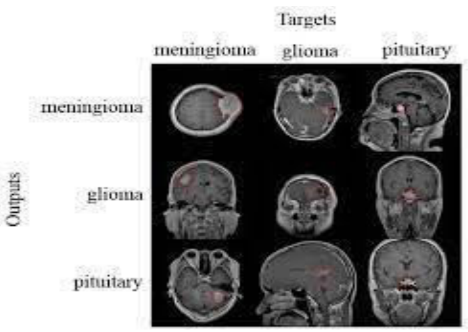

Figure 1 Different types of brain tumours

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II. RELATED WORK

In the recent years,Brain tumor identification is really challenging task in early stages of life. But now it became advanced with deep-learning. Now a day's issue of brain tumor automatic identification is of great interest. In Orderto detect the brain tumor of a patient we consider the data of patients like MRI images of a patient's brain.

[1] In the year 2015, Mikael Agn, Oula Puonti, Ian Law proposed brain tumor segmentation by a generative model with a prior on tumor shape in which they present a fully automated generative method for brain tumor segmentation in multi-modal magnetic resonance images. They base the method on the type of generative model often used for healthy brain tissues, where tissues are modeled by Gaussian mixture models combined with a spatialtissue prior. They extend the basic model with a tumor prior, which uses convolutional restricted Boltzmann machines to model tumor shape. Experiments on the 2015 and 2013 BRATS data sets indicate that the method's performance is comparable to the current state of the art in the field, while being readily extendable to any number of input contrasts and not tied to any specific imaging protocol.

[2] In another study in the year 2017, Diederik P. Kingma, Jimmy Lei Ba developed Adam, an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments. The method is straightforward to implement, is computationally efficient, has little memory requirements, is invariant to diagonal rescaling of the gradients, and is well suited for problems that are large in terms of data and/or parameters. The method is also appropriate for non-stationary objectives and problems with very noisy and/or sparse gradients. The hyper-parameters have intuitive interpretations and typically require little tuning. Some connections to related algorithms, on which Adam was inspired, are discussed. We also analyze the theoretical convergence properties of the algorithm and provide regret bound on the convergence rate that is comparable to the best known results under the online convex optimization framework. Empirical results demonstrate that Adam works well in practice and compares favorably to other stochastic optimization methods. Finally, we discuss AdaMax, a variant of Adam based on the infinity norm.

[3] In the year 2018, Manda SSSNMSRL Pavan proposed Brain tumor segmentation methodology is based on Convolutional Neural Networks (CNN), by exploring into small 3x3 kernels. The employment of small kernels permits coming up with a deeper architecture, besides having a positive impact against over fitting, given the less variety of masses within the network and also investigating on the utilization of intensity normalization as a pre- processing step, which is not common in Convolution Neural Network based segmentation methods, and well-triedin conjunction with information augmentation to be intolerably in effect for neoplasm segmentation in magnetic resonance imaging pictures.

II. EXISTING SYSTEM

Manual segmentation of brain tumors from large MRI images is a difficult and time-consuming task. Generative models require prior information and segmentation of brain tumors, whereas discriminative models depend on a set of features and classifiers .The most commonly adopted classifiers are support vector machines(SVM), random forests, neural networks and genetic algorithms.

III. LIMITATIONS

In the existing system, we can only detect whether the patient possess brain tumour or not but in the proposed systemwe can also the classify the type of brain tumour. The main disadvantages of the existing system are instabilities, overfitting problems and less accuracy which can be overcome by the proposed system.

IV. PROPOSED SYSTEM

In the proposed system,we are providing new methods of MRI images of Brain of a patient. Here pre-processing is done by Gaussian which is a linear filter. Then feature Extraction is done for the images by GLCM features. Finally classification applied through an algorithm Convolutional neural networks which will identify the tumor regions.Region based Two-Pathway-Group CNN architecture for brain tumor segmentation,which exploits local features and global contextual features simultaneously.This model enforces equivariance in the Region based Two-Pathway CNN model to reduce instabilities and over fitting parameter sharing. Finally, we embed the cascade architecture into Region based Two-Pathway- Group CNN in which the output of a basic CNN is treated as an

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additional source and concatenated at the last layer CNN into a two pathway architecture improved the overall performance over the currently published state-of-the-art while computational complexity remains attractive.

Figure 2 describes the architecture diagram of the proposed system and list the overall modules of the proposed system

Image Acquisition:

The Primary Phase is acquiring images. After the Images collection, the obtained images have to be prepared with a wide range of vision. First capture the input images from available source.

Image Preprocessing:

The images which are collected are subjected to pre- processing.In Pre-processing stage basic steps are image resizing and applying Gaussian filters for a perfect input clear image for easy identification of an image. Pre- processed images will be segmented digitally into various pixels. We do this segmentation for an image is to modifyits representation to have more clarity to analyze the images.

Image Segmentation:

In the feature extraction process, we can implement the effective texture operator which labels the pixels of animage. Here we extract the features and characteristics of Images for easy detection of brain tumor.

Convolutional Neural Networks:

Convolutional neural networks algorithm is used for classification of brain images. It is produce the best results forthe image.

Tumor Detection:

Finally, analyze the image using filters and Convolutional neural networks algorithm to detect the tumor or Non-tumor.

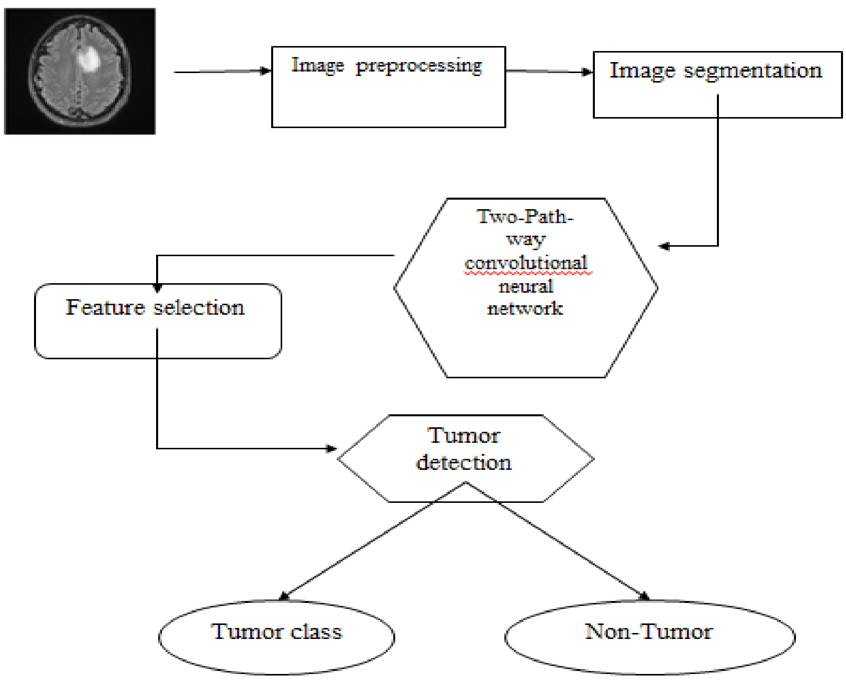

Figure 2.ARCHITECTURE DIAGRAM

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V. ADVANTAGES

The Two-Pathway CNN model gives better accuracy when compared to the existing model. After detectingthe existence of tumour, it also helps us to find which type of tumour the patient possesses.

VI. EXPERIMENTAL RESULTS

Figures shows the results of Detecting and classifying the type of Brain Tumour using Deep learning techniques based on Convolutional neural networks algorithm. Figs. 1, shows the dataset of the brain tumor images and Figs.2,displays the training of the dataset images. Figs.3,displays the output of the given MRI image.

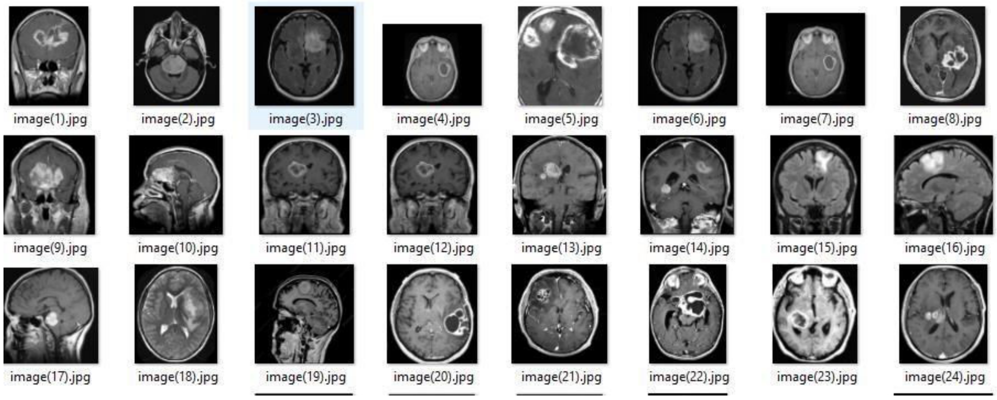

Figure 3. Dataset of the brain tumor images

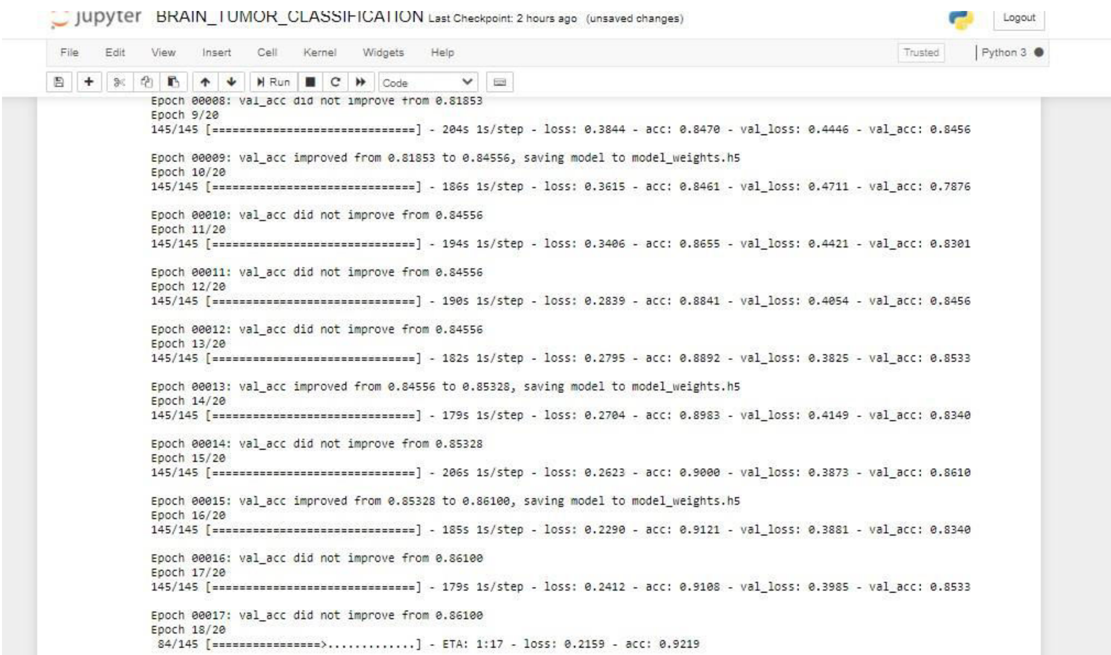

Figure 4. Training of the dataset images

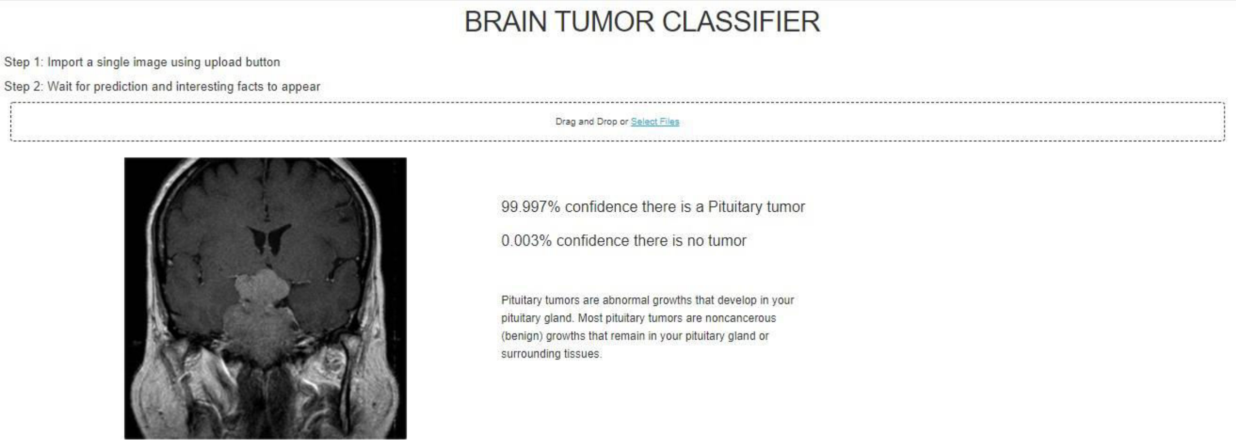

Figure 5.Output of the given MRI image

VII. CONCLUSION

This paper presents the summary of the research and the work consists of four phases. Image division process assumes a significant job in therapeutic Image handling. Right now, this work,we proposed a DNN structure for Brain Tumor order of information utilizing stacked auto encoders. The DNN is manufactured utilizing stacked autoencoders fell with soft max classifier. The HFEs (GLCM, HOG, and LBP) removed the ideal element esteems from fragmented area. At that point, the element choice strategy was applied to the component extraction
information for best element choice. At last, the suspicious bits were ordered by utilizing stacked auto encoder DNN classifier dependent on chose highlights. Our model is contrasted and a few neural system draws near and other condition of craftsmanship approaches in the writing. From the outcomes it is obvious that our model outflanks other model with a precision of 95.3%. Besides, our model gives accuracy estimation of 93.7% and review of 92.2%
%, which is a lot of promising to recognize the unusual Brain tumors order from understanding MRI Image, and the proposed strategy can be utilized to group the different kinds of tumor concurring through therapeutic analysis framework. In view of the investigations and perceptions it is presumed that the proposed DNN system for Brain Tumor grouping can be utilized as integral asset for the infection analysis process. Our model aides in foreseeing the Brian Tumor of a patient with better exactness, particularity, accuracy and review which are significant in the restorative world.In future, the proposed work can be extended with different types of modalities for detecting the tumors and the optimization technique uses to increase the classification accuracy.

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