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Classification of brain tumor image based on High Grade and Low Grade using CNN with LSTM

S. Rukmani Devi [1], Dr. P.Selvaraju [2]
[1]*Research scholar, Bharathiyar University, Coimbatore, Tamil Nadu, India.*
[2] *Professor & Head of Department, Department of Computer Science, Veltech MutiTech College of Engineering, Chennai, Tamil Nadu, India..*

Abstract

Magnetic resonance imaging (MRI) is a normally available imaging method for the examination of these cancers or tumors, but the vast amount of data provided by MRI prohibits within a reasonable time restricting by manual segmentation based on the procedure of precise quantifiable measurements in medical practice. Gliomas are the most prevalent and destructive brain tumors, resulting at its highest grade in a very small life of expectancy. In general, gliomas can be classified into High (HG) and Low (LG) Grades. The precise diagnosis of the glioma allows to define the progression of the infection and to choose the therapeutic plan. Although classification of medical images has attained remarkable success using a Convolution Neural Networks (CNNs), but it is dispute for finding out the medical image exactly over 3D. This paper has proposed to evaluate the CNN with Long Short Term Memory (LSTM) for analyzing glioma of LG and HG 3D brain tumor image. In order to classify the volume of 3D brain tumors, the pre-trained VGG-16 gets extracted and served into LSTM for learning higher level features while feature extraction. Based on the results produced by this method, the best method is suggested for brain tumor identification and further, for analysis of MRI images.

Keywords: *brain tumor, Gliomas, CNN, LSTM, MRI.*

1. Introduction

GLIOMAS are one of the tumors that begin with brain in glial cells which have the greatest mortality rate and occurrence levels. Such the neoplasms can be classified into Low Grade Gliomas (LGG) and High Grade Gliomas (HGG), with the previous less violent and infiltrative than the latter [1]. Patients even under care do not last longer than 14 months following diagnosis on average. Existing treatments require, or a mixture of surgery, radiation, radiotherapy. Currently, the treatment of a brain tumor is based on modalities of neural imaging, especially CT and MRI [2]. CT scan utilizes X-rays from different angles to yield a sequence of images of the brain. In order to raise the color difference of image, dye is injected into veins. Once the irregular cell growth is detected by CT the patient is sent for MRI scan [3]. It is the broad spatial resolution comparison with CT based on the modality of non-invasive and non-ionizing imaging. Gliomas typically have a distinctive presence in systemic MRI. MRI is particularly useful in clinical practice for detecting gliomas, as it is possible to obtain MRI transcripts that provide additional information [4]. The precise gliomas segmentation and their structures of intra-temporal are not only significant for handling planning, but also for evaluations can follow-up. Though the segmentation by manual takes time-consuming and prone to challenging classification of inter and intra rater faults [5]. So usually doctors use rough measurements for evaluation. Precise, automatic or semi-automatic methods are needed for these reasons. Nevertheless, since the form, function, and position of these irregularities are highly variable and also it is a challenging task. Furthermore, the influence of the tumor mass affects the structure of normal tissues around it. MRI images may also pose certain issues namely inhomogeneity of strength, or specific levels of intensity among the acquisition and same sequences scanners. The HG glioma usually does not have strong boundaries and also have the swollen area around a tumor and appear heterogeneous [6]. With the little bulge and cyst portion in a tumor, LG Gliomas have strong and fine confined borders. On FLAIR and T2-w images, tumors are distinguished by a hyper intense lesion in conjunction with improved hyper intensity and T1-w

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images [7]. In this proposed work, we considered a frame work of fully automatic to classify the LGG and HGG using a cascaded NN consisting of CNN and LSTM.

The organization of this paper is as follows. In section 2 described the associated review based on classification of deep learning. In section 3 described the materials and methods based on data collection, pre-processing, segmentation, feature extraction based CNN architecture and classification of LSTM. In section 4 described the CNN models with enhanced performance and deeper design using LSTM classification In section 5, whereas the conclusions are presented in the last Section.

2. Literature Review

The survey based on ordinary or irregular cerebral tumor categorization and segmentation, DL is most widely used for brain tumor examination in various circumstances. Gliomas are the most identified tumors in the brain. Many cancers can be less harmful because of the low grade. For many years patients with such tumor may survive [7]. In many other cases may have a duration of survival has not exceeding two years for some HG tumors which are highly destructive [8]. Most of these tumors have low contrast and structures which are infected with edema [9]. There are a number of DL building blocks the scientists have used in recent times to segment the brain tumor. Some of those blocks include deep neural convolution networks (DCNNs) whereas RNN is constructed on data from sequences. S. Grivalsky et,al.[10] pick dataset of BraTS-17 based on the suggested RNN design to conduct HGG segmentation. LSTM is an improved version of RNNs which has been intended for sequence data design [11]. Stollenga et,al.[12] also suggested incredible Pyramidal Multi-Dimensional LSTM (PyraMiDLSTM) structures to use a very remarkable topology based on tumor segmentation. The technique is easier to parallelize and requires less measurements which has to works well on 3D images and GPU architectures [13]. MRBrainS13 dataset has achieved good segmentation results. LSTMMA [14] described to utilize the segmentation based on multimodality. The CNN models are exceeding 100 layers by gradually perplexing with some frameworks showing a large quantity of loads and trillions of neuronal families [15-16].

The process of Hough-CNN [17] is introduced using the deliberative qualities of CNNs to cope with chosen divisions [18]. S. Hussain et,al.[19] has proposed CNN based five approaches for brain tumor segmentation. S Pereira et,al. [20] proposed by each with the scale of 3x3 using mini-kernel CNN. K Kamnitsas et,al. [22] described to classify their CNN based on 3D software as Deep Medic. Extraction of multi-class brain tumors are used by cascaded CNN [23]. A new strategy for brain tumor separation is suggested by integrating a Fully-CNN post-treatment activity with Conditional Random Fields (CRF) [21, 24, 25], which has different to collecting CRF. It can be prepared in three steps, namely individual picture, cuts individually and fixes [26]. To address the problem of brain tumor division, three distinctive 3D CNN models are investigated [27, 28]. S Pereira et,al. proposed the Leaky Rectifier Linear Units (LRLU) [29] for tumor segmentation in their CNN model. CNN Input Cascade used to divide the tumor using fully programmed strategy of DL [30]. I. Shahzadi et,al described by using LSTM and CNN cascade to identify tumors[31]. VGG-16 is used as pre-trained for CNN and this network outcome has supplied to LSTM network. The suggested deep model trained by SVM classifier which obtains the deep features. YPanuses CNN to grade brain tumors [32]. A earlier pre-trained CNN model named AlexNet is used in a work by Yan Xu[33] to gather deep features for classification of tumors. In another study [34], CNN is also used to identify the tumor from 3,064 weighted with T1 images[35-38].

3. Materials and Methods

Segmentation of the brain tumor attempts to distinguish healthy tissue from disease areas namely the progressing tumor, the necrotic heart and the underlying edema. Diagnosis and treatment preparation is an essential step, both of which need to take place immediately to increase the probability of successful treatment in the case of a malignancy[39-42]. There is a

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high request for computer processes because of the slow and tedious process of manual segmentation, which can do this quickly and accurately. In our system consists of two components for volumetric MRI brain tumor classification image namely, CNN based feature extraction of pre-trained VGG-16 and LSTM for glioma classification into LG and HG as shown in figure 1.

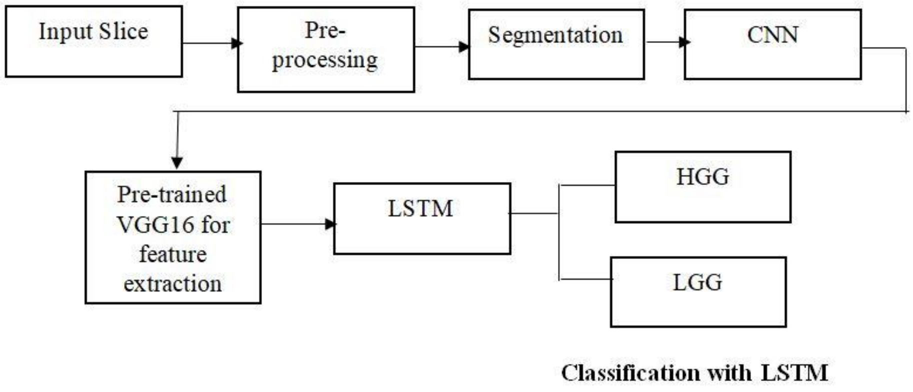

Figure.1 Classification of brain tumor into LG and HG glioma

3.1 Dataset

MRI data was collected by the 2015 from MICCAI BraTS Challenge. It contains of approximately 250 HG glioma cases and 50 LG cases. Each dataset contains four different MRI pulse sequences, each of which is contained for a total no of 620 images per patient on 155 brain slices. Figure 2 is an example of a scan with the ground truth segmentation. The segmentation labels are represented as follows.

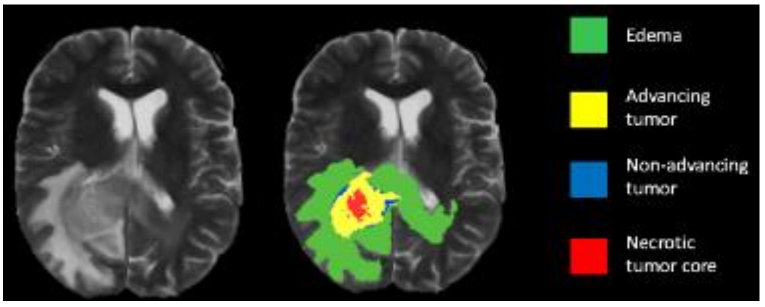

Figure 2: Ground truth segmentation overlay on a T2 weighted scan

3.2 MRI pre-processing

One of the difficulties of interacting with MRI data is coping with objects created either by magnetic field inhomogeneity or by the patient's small movements during the scanning process. Possibly there will be a bias throughout the subsequent images which can distress the results of the segmentation mainly when establishing the computer-based models in figure 3.

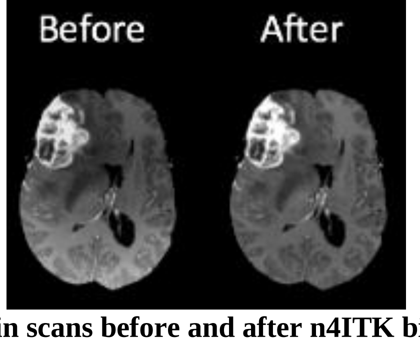

Figure 3: Brain scans before and after n4ITK bias correction

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Notice the higher intensity at the bottom of the image on the right. This can be a source of false positives in computer segmentation. The images of T1 and T1C in the dataset used an n4ITK bias correction which removed for each sample based on intensity gradient. Further pre-processing method can allows the pixel intensities to be standardized; since MRI intensities are measured in variable units can differ significantly between the devices used and the scan times [42-44].

3.2.1 Pulse of sequence

There are numerous sets of RF signals which can be used to various kinds of tissue. There are frequently four separate sequences developed for sufficient segmentation namely T1-contrast, Fluid Attenuated Inversion Recovery (FLAIR), T1 and T2 are shown in Figure 4. Each of these series of pulses based on various tissue types uses the distinct physiological and chemical properties, resulting in a distinction among the different modules. Notice the difference of intensities between the 4 images in Figure 4, illustrate the images taken from separate pulse patterns of the same brain.

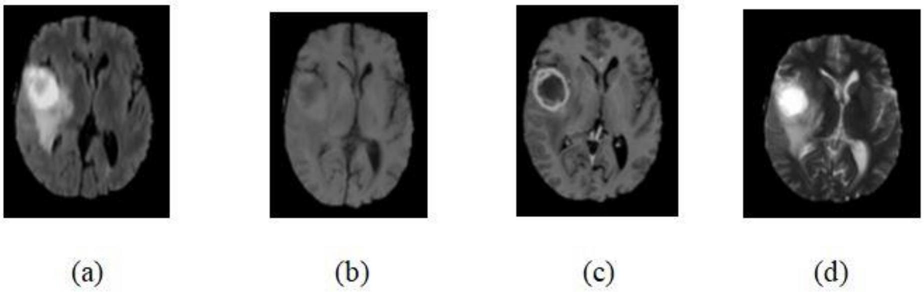

Figure 4: (a) Flair, (b) T1, (c) T1C and (d) T2 sequences of pulse

3.3 Segmentation

Automatic tumor segmentation has the potential to decrease lag time between diagnostic tests and treatment by providing an operative and standardized report of tumor location in a fraction of the time it would take a radiologist to do so

3.3.1 HGG

Typically, HG malignant brain tumors have a small life expectancy with minimal treatment options. The destructive nature of this disorder needs careful identification and treatment planning in order to recover the excellence of patient existence and to prolong it. This importance increases the needs for effective and fast automated methods of segmentation in clinical settings. However, algorithmic segmentation has established to be a challenging job based particular tumors, largely because they appear to be very mechanically and spatially complex. The tumor segmentation of HGG are illustrated in figure 5.

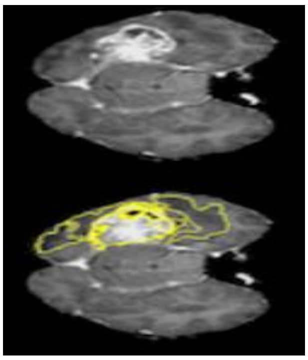

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Figure 5 HGG, tumor segmentations are sketched on the bottom images

3.4 Convolutional Neural Network (CNN)

CNN has been used to get some outcomes of well-known contest and few breakthrough results. Usage of convolution layers consists of transforming a signal or a kernel image to acquire function maps. Hence the unit in a function map is related through the weights of the kernels to the previous node. In training phase, the weights of the kernels are modified by back propagation to improve certain features of the input. Since all units of the same function maps share the kernels, convolution layers have fewer weights to learn than dense FC layers, rendering on CNN simpler to train the model and less susceptible to over fit.
In the sense of CNN the following principles are essential:

1) Initialization: Convergence is necessary to accomplish and use the initialization Xavier. It holds the gradients and activations in stable ranges, else back-propagated grades would disappear or burst.

2) Activation Function: It is mainly for converting the non-linear data. Rectifier Linear Units (ReLU), described as having been found to attain best outcomes than the further hyperbolic tangent or conventional faster training and sigmoid functions are specified in equation 1 and 2.

$$f(x) = \max(0, x) \quad \text{……………………}(1)$$

$$f(x) = \max(0,x) + \alpha \min(0,x) \quad \text{……………………..}(2)$$

Where ‘α’ represents the leakiness parameter and last layer of FC utilized the softmax.

3) Pooling: The feature maps combine the features nearby spatially. This grouping of potentially redundant features creates the demonstration of additional invariant and compact to minor changes in the image namely, insignificant details and also it reduces the next stages of computational load.

4) Regularization: Reduces over fitting. With likelihood ‘p’ it eliminates nodes from the network in each training phase. In this way, it pushes all nodes to acquire improved demonstrations of the data in the layers of the FC, thereby preventing nodes from co-adapting. Both nodes are used at test time.

5) Data Increase: This can be used to decrease over fitting and to increase the size of training sets [26]. Then the patch class is accessed by the central voxel and limited to rotational operations by increase of data. Several scholars still find the image translations but this outcome in the patch being assigned a wrong class for segmentation [26]. Therefore, during the preparation, we expanded our data set by making novel patches in order to rotating the initial patch. In our proposed method introduced a multiple of 90° angle.

6) Loss function: In this function should be reduced while in training stage. The Categorical Cross-entropy was used in equation 3

$$H = -\sum_{j\in voxels}\sum_{k\in classes} a_{j,k} \log(\bar{a}_j, k) \quad \text{……………………}(3)$$

Where ‘ā’ is the probabilistic prediction (after the softmax), and where ‘c’ represents the target. Then explore the design and preparation of our CNN in the next subsections.

7) Architecture: This can be used for reliable method of segmentation though; brain tumors show considerable variation in intra-tumor frameworks, which makes difficult issue in rendering segmentation. We developed a CNN to that the difficulty and adjusted the transition of strength normalization for each tumor grade namely LGG and HGG.

3.4.1 Feature Extraction based VGG-16

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There are already a range of CNN versions with deeper design and improved performance. Hence there are difficult to train deeper networks due to millions of training parameters and requires huge amount of data. The occurrence of precisely labeled, dataset of large-scale is very vital for the additional accurate and generalizable models. But there is no large-scale labelling data set available in the medical imaging issue. The transfer learning strategy is used to overcome this problem where the model on large-scale natural image dataset is first pre-trained e.g. ImageNet.

3.5 LSTM for classification

LSTM is a Neural Network (NN) is mainly based on Recurrent Neural Network (RNN) that can be used to model temporal dependences. It is an iterative loop among the RNN units which can able to store internal hidden states that assist for modeling the behavior of dynamic temporal. Moreover, LSTM act as an extended RNN version with three gates namely Input, forget and output whereas there are two hidden layer present in the NN which consists of 100 nodes are placed on every layer. With these gates LSTM in temporal context knows the long-term dependencies. LSTM has easier to enhance and propagate through the hidden layer since these gates allow the features of the input without affecting the outcome. It has capability to deal effectively with the issue of disappearing gradients because it unlocks certain memory positions in a spatial context that are not useful in determining the final labels for classification. The functionality from the HG and LG volumetric MRI data are in this research reference to LSTM. LSTM's temporal path is filled by the slices within the volume of each subject.

4. Results and Discussion

As more advances are made this section will be updated. A representative example of tumor segmentation on test data is displayed in Figure 6. The model can identify each of the four classes with a good amount of accuracy, with the exception of class boundaries, which are smoother in my prediction than the ground truth.

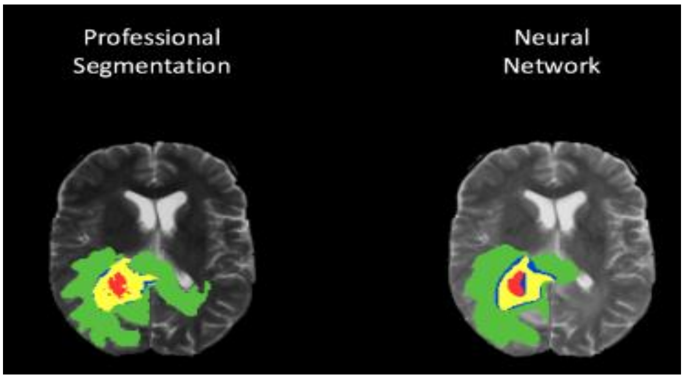

Figure 6 Results of CNN model segmentation

There are currently a lot of CNN versions with better performance and a broader design. Table 1 describes their requirements on some of the growing architectures. Pre-trained on Image Net, VGG16 network are used for extracting the features in this research which get utilized as a LSTM input signal. However, there are 16 layers in term of 3x3 with a stride over convolutional layer and 3 Fully Connected (FC) layer whereas kernel used as filter in the VGG-16 is available with small sized multiple sets which may improve the network depth for empowering the network to extract features with highly complex at low cost. The comparison based on VGG-16 as function extractor with AlexNet is carried out in this study.

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Table.1 Comparison of CNN architecture based Pre-trained VGG16 and AlexNet

Architecture	VGGNet	AlexNet
Layers	16	5
Input image slice	225x225x3	221x221x2
% error	6.3	14.2

Glioma classification in the proposed method is conducted in LG and HG dependent on function derived from MRI with FLAIR classification and the performance metrics utilized is accuracy. In order to detect the data of volumetric 3D MRI brain tumor, FC7 has utilized as feedback technology to two layers of LSTM. Table 2 outlines important approaches for glioma diagnosis and the output matrices. Precision values obtained in previous work in glioma classification literature are moderately high with the maximum precision recorded as 93%. Nevertheless, with a limited number of samples, our approach has achieved a similar outcome and has an accuracy of 84 % with VGG-16. We distinguish between the volumes in the suggested binary class problem for HG and LG glioma.

Table 2 Results of Glioma classification of CNN architecture with LSTM

CNN-LSTM Model	Training/Testing	Accuracy (%)
VGGNet-LSTM	Hold out (70-10%)	70%
AlexNet-LSTM	Hold-out (80-20%)	85%

5. Conclusion

In this paper produces promising results, an implementation like this leaves no room for faults or false positives. It is necessary to extract as much of the tumor mass as practicable in an operation environment without destroying around the healthy tissue. In this research, cascaded CNN-LSTM is suggested as a brain tumor volumetric group of brain tumor in term of LG and HG glioma. In our experimental results have shown that the VGG-16 model on state-of - the-art CNN designs performs greatest by collecting the high-level demonstrations of features and it assist the LSTM for capability differentiate among glioma of LG and HG. The test has shown that VGGNet achieves greater accuracy through more precise extraction of the function. They distinguish between the volumes in the suggested binary class problem for HG and LG glioma. The AlexNet 70% and VGGNet 85% of accuracy test.

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