Brain Tumor Classification using Convolutional Neural Network

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Abstract –

Brain tumor diagnosis requires high accuracy, where minute errors in judgment may lead to critical problems. For this reason, brain tumor segmentation is an important challenge for medical purposes. Currently several methods exist for tumor segmentation but they all lack high accuracy. Here we present a solution for brain tumor segmenting by using deep learning methodology. In this work, we studied different brain MR images and applied segmentation on each to classify them as benign or malignant using convolutional neural network technique. .

Keywords: Convolutional neural   network, Kaggle, Anaconda, Python, Jupyter Notebook, Medical image analysis, Deep learning.

I INTRODUCTION

Tumor is generally a medical term given to the irregular growth of tissues. Brain tumor is an irregular mass of tissue in which cells grow uncontrollably, seemingly unchecked by the mechanisms that control normal cells. Brain tumors can be either malignant or benign based on whether they are cancerous or not respectively. Magnetic resonance imaging (MRI) is a image technique that is used in medical field to get images of the anatomy. MRI scanners use magnetic resonance concepts to generate an image of the organs in our body. Health care professionals use MRI scans to diagnose a variety of conditions, from torn ligaments to tumors. From these high-resolution images, we can derive the abnormal cells present in our brain tissues. MRI portrays clearly every required detail without radiation unlike X-ray process. It is adaptable method since a contrast between one tissue and other can be changed through imaging techniques. For example by changing the gradient pulses it is possible to produce images with high contrast. These days there are various methods for classification of MRI image such as fuzzy method, neural networks, and variation segmentation. Medical image processing method has provided lots of methods which help to automate the task of classification in less time span and with more accuracy. The very important steps in medical image processing are Feature extraction and Feature selection, Image segmentation and Image classification. Feature selection is even more important than feature extraction because generalized subset is needed to get less computation time and high accuracy. Most of the methods that are used for classification of brain tumor's are solely based on segmentation. Hence only less importance is given to the problem of classification and feature extraction which are not only the most important step but can also improve help to improve the performance of CAD. These techniques are now combined with image processing techniques to give best of results in the diagnosis of many critical diseases such as lung cancer and image analyzation of breast cancer. Though Machine learning techniques proved to be useful, in recent times the need for more accuracy and real time process forced to user to venture into a new field, Deep Learning owing to its superior models. Recently, Deep learning techniques have a major foothold in the fields of medical

analyzation, object recognition system, and object detection. In DL, the accuracy and efficiency of data model depends on its given datasets and training. To overcome the training process and to get better timed results DL adopts a concept called as transfer learning. Transfer learning is a DL technique in which trained features of large data can be deployed to small data sets. Time saving is the major cause that lead to the usage of Pre trained models. These pre trained models doesn't need large datasets to obtain the desired results. This paper is divided and organized into seven sections. Section 2 provides literature review, while section 3 describe proposed system. Section 4 describes the Performance metrics. Section 5 illustrates the results .Section 6 provides concludes the whole discussion and present the future work and references.

II LITERATURE REVIEW

A literature review in a project report is the section which portrays the various analyses and research made in the field of your interest and the results already published, taking into account the various parameters of the project and the extent of the project. It is the most important part of your report as it gives you a direction in the area of your research.

Jayashree Kalpathy-Cramery et al [1] in 2016 reported the set-up and results of the Multimodal Brain Tumor Image Segmentation Benchmark (BRATS).Twenty state-of-the-art tumor segmentation algorithms were applied to a set of 65 multi-contrast MR scans of low- and high-grade glioma patients – manually annotated by up to four raters – and to 65 comparable scans generated using tumor image simulation software. Quantitative evaluations revealed considerable disagreement between the human raters in segmenting various tumor sub-regions (Dice scores in the range 74-85%), illustrating the difficulty of this task. We found that different algorithms worked best for different sub-regions (reaching performance comparable to human inter-rater variability), but that no single algorithm ranked in the top for all sub regions simultaneously.

Li Wang et al [7] in 2017 proposed a novel patch-driven level sets method for segmentation of neonatal brain images by taking advantage of sparse representation techniques. Specifically, we first build a subject-specific atlas from a library of aligned, manually segmented images by using sparse representation in a patch-based fashion. Then, the spatial consistency in the subject-specific atlas is further enforced by considering the similarities of a patch with its neighboring patches. Finally, this subject-specific atlas is integrated into a coupled level set framework for surface-based neonatal brain segmentation. The proposed method has been extensively evaluated on 20 training subjects using leave-one-out cross validation, and on 132 additional testing subjects. Both quantitative and qualitative evaluation results demonstrate the validity of the proposed method.
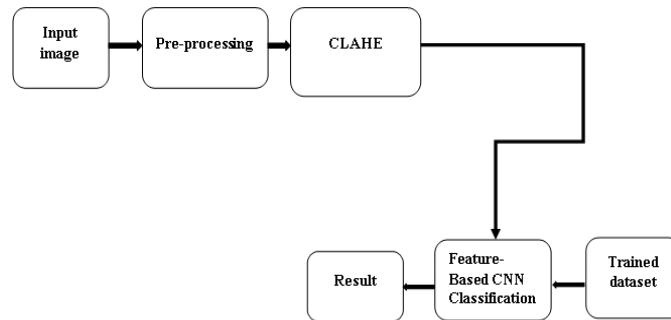
Li Wang et al [6] in 2017 employed the random forest technique to effectively integrate features from multisource images together for tissue segmentation The multi-source images include initially only the multi-modality (T1, T2 and FA) images and later also the iteratively estimated and refined tissue probability maps of gray matter, white matter, and cerebrospinal fluid. Experimental results on 119 infant subjects show that the proposed method achieves better performance than other state-of-the-art automated segmentation methods, with significantly reduction of running time from hours to 5 minutes.

Chunming Li et al [8] proposed a novel region-based method for image segmentation, which is able to deal with intensity inhomogeneities in the segmentation. First, based on the model of images with intensity inhomogeneities, we derive a local intensity clustering property of the image intensities, and define a local clustering criterion function for the image intensities in a neighborhood of each point. In a level set formulation, this criterion defines an energy in terms of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity inhomogeneity of the image. Therefore, by minimizing this energy, our method is able to simultaneously segment the image and estimate the bias field, and the estimated bias field can be used for intensity inhomogeneity correction (or bias correction). Our method has been validated on synthetic images and real images of various modalities, with desirable performance in the presence of intensity inhomogeneities.

Kyong Hwan Jin et al [11] propose a novel deep convolutional neural network (CNN)-based algorithm for solving ill-posed inverse problems. Regularized iterative algorithms produce excellent results, but can be challenging to deploy in practice due to factors including the high computational cost of the forward and adjoint operators and the difficulty of hyperparameter selection. The starting point of this paper is the observation that unrolled iterative methods have the form of a CNN (filtering followed by point wise nonlinearity) when the normal operator (H^*H, where H^* is the adjoint of the forward imaging operator, H) of the forward model is a convolution. Based on this observation, we propose using direct inversion followed by a CNN to solve normal-convolutional inverse problems. The proposed network outperforms total variation-regularized iterative reconstruction for the more realistic phantoms and requires less than a second to reconstruct a 512×512 image on the GPU.

III PROPOSED SYSTEM

In this paper, we present an automatic brain tumor segmentation technique based on Convolutional Neural Network. The main contribution of our paper is the diagnosis of type of tumor based on the captured MRI scan images. All previous works on the dataset that we are working with are for classification of tumor types. All the previous research performed on this dataset is not intended for segmentation. The accuracy was improved a lot than the existing systems using this method. We can obtain high confidence percentage by this method.

```
┌──────────┐     ┌──────────────┐     ┌────────┐
│  Input   │ ──► │ Pre-processing│ ──► │ CLAHE  │ ──┐
│  image   │     │              │     │        │   │
└──────────┘     └──────────────┘     └────────┘   │
                                                    │
                                                    ▼
┌──────────┐     ┌──────────────┐     ┌──────────┐
│  Result  │ ◄── │ Feature-     │ ◄── │ Trained  │
│          │     │ Based CNN    │     │ dataset  │
│          │     │ Classification│    │          │
└──────────┘     └──────────────┘     └──────────┘
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Preprocessing:

Data pre-processing is an important step in the data mining process and it is the most important phase of a machine learning project, especially in computational biology. If there are more irrelevant and recurring information or noisy and unreliable data present, then discovery during the training phase will become more difficult. Hence we perform the preprocessing on the given MRI image. Data preparation and filtering steps can take considerable amount of processing time. Data pre-processing includes cleaning, Instance selection, normalization, transformation, feature extraction and selection, etc. The product of data pre-processing is the final training set.

Blurring:

Blurring is used in preprocessing steps, where removal of small details from an image prior to object extraction, and bridging of small gaps in lines or curves is needed. The idea of this process is replacing the value of every pixel in an image by the average of the gray levels in the neighborhood defined by the filter mask.

Adaptive Histogram Equalization:

Histogram Equalization is a computer image processing technique used to improve contrast in images. It accomplishes this by effectively spreading out the most frequent intensity values, i.e. stretching out the intensity range of the image. This method usually increases the global contrast of images. Adaptive Histogram Equalization differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image.

CLAHE:

Contrast Limited AHE (CLAHE) differs from adaptive histogram equalization in its contrast limiting. In the case of CLAHE, the contrast limiting procedure is applied to each neighborhood from which a transformation function is derived. CLAHE was developed to prevent the over amplification of noise that adaptive histogram equalization can give rise to. Contrast Limited AHE (CLAHE) is a variant of adaptive histogram equalization in which the contrast amplification is limited, so as to reduce this problem of noise amplification. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighborhood region.

CNN:

In machine learning, a convolutional neural network (CNN, or ConvNet) is a class of deep, feed-forward artificial neural networks that has successfully been applied to analyzing visual imagery. CNNs use relatively

little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

Classification:
Classification tasks usually involve separating data into training and tasting sets. Each instances in the training set contains one target value (i.e. the class labels) and several attributes (i.e. the features).

IV PERFORMANCE METRICS

To validate the performance of the proposed system and to find out the efficient model, we calculate various parameters such as accuracy, precision, recall and F1 score.

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recal = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Where ``TP'' describes true positive, ``TN'' represents true negative, ``FP'' indicates to false positive, and ``FN'' denotes false negative.

V RESULT

This section contains the code of the proposed project along with the accuracy calculation of each training data set. The three images attached includes a importing, training and feeding data to a model.

VI CONCLUSION:

This paper discussed the application of deep learning models for the identification of brain tumor. We used a CNN pre trained model which was chose based on various parameters which was used for the segmentation of MRI scanned images which was fed as input. The final result showed that the MRI brain scan which was given contained cancerous tumor(malignant) or not (benign).

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