LEVERAGING DEEP LEARNING APPROACHES FOR BRAIN TUMOR IDENTIFICATION

[1]S.Sravan Kumar, [2]Yanagandhula Varun, [3]Inapanuri Kavya,[4] Neela Sunil

Assistant Professor in department Of IT Teegala Krishna Reddy Engineering College

sravanreddysathu@gmail.com

UG Scholars In Department of IT Teegala Krishna Reddy Engineering College

[2]varunyanagandhula1922@gmail.com ,[3] kavyainapanuri21@gmail.com ,[4] sunilneela1@gmail.com

Abstract

A brain tumor is a growth of cells in the brain or near it. Brain tumors can happen in the brain tissue. Brain tumors also can happen near the brain tissue. Nearby locations include nerves, the pituitary gland, the pineal gland, and the membranes that cover the surface of the brain. Although MRI images are a popular imaging method for evaluating these tumors, the volume of data it generates makes it difficult to manually segment the images in a reasonable amount of time, which restricts the use of precise quantitative assessments in clinical settings. The enormous spatial and structural heterogeneity among brain tumors makes automatic segmentation a difficult task, hence dependable and automatic segmentation methods are needed. This project focuses on developing deep learning models based on convolutional neural network and watershed algorithms to perform the automated semantic image segmentation of the MRI images of the brain. We explore the current state of the CNNs architecture and evaluate them on the BraTS dataset. Different regularization methods and hyper parameters are tested and optimized through a series of experiments. Finally, a web application is created so that the developed models can be used easily by medical practitioner.

I INTRODUCTION

A brain tumor is a development of abnormal cells in the brain that multiply uncontrollably. Since the human skull is a rigid and volume-limited structure, any unanticipated development may have an impact on a human function depending on the area of the brain involved. It also has the potential to spread to other bodily organs and have an impact on human functions. Brain tumors can be benign (non-cancerous) or malignant (cancerous). As stated in, brain and other nervous system cancer is the tenth largest cause of death, with a five-year survival rate of 34% for males and 36% for women for those with cancer of the brain. The most common type of brain tumor 2 found in adults is glioma which starts from the glial cells. According to WHO these tumors are categorized in 4 types ranging from I to IV in terms of severity. Types III and IV gliomas are high-grade gliomas that nearly always result in death, whereas Types II and I low-grade gliomas grow more slowly and have a longer life expectancy, hence vigorous treatment is frequently postponed as long as possible. As a result, earlier diagnosis of brain tumors can substantially improve options for treatment and increase the likelihood of survival.

Image segmentation is the process of partitioning an image into well-defined regions or categories, each of which comprises pixels with comparable qualities and is designated to one of these categories. Similarly, brain tumor segmentation is the process of separating the timorous from the non-timorous regions of the brain. MRI is the standard technique for brain tumor diagnosis as it is non-invasive and provides good soft tissue contrast with high spatial resolution. Improved disease diagnosis, treatment planning, monitoring, and clinical trials all depend on the segmentation of brain tumors from neuroimaging modalities. To determine the location and size of the tumor, accurate brain tumor segmentation is necessary. However, the characteristics of brain tumors make accurate segmentation challenging. These tumors can develop in practically any area and come in a wide range of sizes and shapes.

The intensity value of a tumor may overlap with the intensity value of healthy brain tissue, and they are typically poorly contrasted. As a result, it is difficult to tell healthy tissue from a tumor. Integrating data from various MRI modalities, such as T1-weighted X-ray (T1), T1-weighted MRI with contrast (T1c), and T2-weighted X-ray, is a typical method to address this problem. Depending on the degree of human interaction during segmentation of the scans, MRI segmentation can be divided into three classes.

It can be classified into semi-automated approaches, completely automatic methods, and manual methods. Precision and speed in treatment planning are critical for enhancing patient quality of life, however manual segmentation is time-consuming due to the enormous amount of data provided by MRI. As a result, approaches for automatic and reliable segmentation are necessary. However, developing automated brain tumor segmentation techniques is technically challenging and even professional raters' manual segmentations exhibit intra-operator variability as tumors can be ill-defined with soft tissue boundaries and lesions deform surrounding normal tissues. Furthermore, the lack of a widely available brain tumor database containing ground-truth segmentations makes it difficult to assess the performance of different techniques in an unbiased manner.

The BraTS (Brain Tumor Segmentation challenge), however, has made a concerted effort in this regard. Artificial neural networks (ANN) and, in particular, convolutional neural networks have been shown to outclass humans in the task of image segmentation and classification. as illustrated by the classification of melanomas. In 2015, Ronneberger et al. published U-Net , a network for segmenting biomedical images. This method outperformed all competing network structures in the ISBI challenge, achieving exceptional results. Since then, the U-Net architecture has been implemented in a variety of fields for segmentation, including the segmentation of brain tumors, where it has demonstrated increasing performance each year in the BraTS challenge.

The purpose of this project is to develop an automated brain tumor segmentation application that uses multimodal MRI images of a patient's brain to generate the segmentation mask. The dataset employed for segmentation is BRATS 20, which comprises four distinct MRI modalities and one target mask file. The intention is to build on top of current state of the art, analyze and evaluate different medical image segmentation techniques, creating easy to use GUI for medical practitioners to perform automatic segmentation of gliomas.

II LITERATURE SURVEY

"Implementation of Brain Tumor Detection using Segmentation Algorithm & SVM"

Swapnil R. Telrandhe et.al.[1], in their work titled as "Implementation of Brain Tumor Detection using Segmentation Algorithm & SVM", implemented the system for brain tumor detection from MRI images, the malignant or benign tumor region we will find by this system. The complete system includes preprocessing of MRI by using Median filtering, skull removal by morphological filtering, and segmentation by k-means algorithm; object labeling by HOG algorithm, also feature extracted by HOG, and linear SVM implementation by using extracted feature of the MRI. The proposed system is the combination of some technologies like k-means for segmentation, HOG for object labeling, median filter, morphological filter and wavelet transform for the preprocessing and skull masking. So the result of this combination is much fairer than the individual of them or some other combination. The linear SVM and HOG work with coordination because the HOG extracts the feature and SVM uses that data for learning the SVM, so the SVM will be able to make the patterns and after training in testing it will work to test the pattern and give the conclusion. The main limitation of this project is less accuracy and SVM can not work well for large data types.

"Review of MRI-based brain tumor image segmentation using deep learning methods"

Ali IúÕn et.al.[2], in their work titled as "Review of MRI-based brain tumor image segmentation using deep learning methods", said that Brain tumor segmentation is an important task in medical image processing. The purpose of their paper is to provide a review of MRI-based brain tumor segmentation methods. Recently, automatic segmentation using deep learning methods proved popular since these methods achieve state-of-the-art results and can address this problem better than other methods. Deep learning methods can also enable efficient processing and objective evaluation of the large amounts of MRI-based image data.Automatic segmentation of the brain tumors for cancer diagnosis is a challenging task. The limitation of this is future improvements and modifications in CNN architectures and addition of complementary information from other imaging modalities such as Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS) and Diffusion Tensor Imaging (DTI) may improve the current methods, eventually leading to the development of clinically acceptable automatic glioma segmentation methods for better diagnosis.

"Advancing The Cancer Genome Atlas glioma MRI collections with expert segmentation labels and radiomic features"

Spyridon Bakaset.al.[3], in their work titled as "Advancing The Cancer Genome Atlas glioma MRI collections with expert segmentation labels and radiomic features", said that Gliomas belong to a group of central nervous system tumors, and consist of various sub-regions. Gold standard labeling of these sub-regions in radiographic imaging is essential for both clinical and computational studies, including radiomic and radiogenomic analysis.The glioma sub-region labels were produced by an automated state-of-the-art method and manually revised by an expert board-certified neuroradiologist. An extensive panel of radiomic features was extracted based on the manually-revised labels. This set of labels and features should enable i) direct utilization of the TCGA/TCIA glioma collections towards repeatable, reproducible and comparative quantitative studies leading to new predictive, prognostic, and diagnostic assessments, as well as ii) performance evaluation of computer-aided segmentation methods, and comparison to our state-of-the-art method. They have cleared from current literature that such advanced image-based phenotyping requires accurate annotations of the various tumor sub-regions. Both clinical and computational studies focusing on such research require the availability of ample data to yield significant associations.

III EXISTING SYSTEM

Existing system they have implemented the system for brain tumor detection from MRI images. This system uses Median filtering for preprocessing of MRI images, segmentation by k-means algorithm. The linear SVM and HOG work with coordination because the HOG extracts the feature and SVM uses that data for learning the SVM, so the SVM will be able to test the patterns.

Disadvantages:

• SVM requires careful feature engineering, where relevant features need to be selected, which can be time-consuming and require domain expertise.

• SVM requires a larger amount of labeled data to achieve comparable performance.

• SVM does not have built-in mechanisms for automatically learning hierarchical features from raw data

IV PROPOSED SYSTEM

The purpose of this project is to develop an automated brain tumor segmentation application that uses MRI images of a patient's brain to generate the segmentation mask and to recognize the tumor.

• CNN takes an input image of raw pixels, and transforms it via Convolutional Layers, Rectified Linear Unit (RELU) Layers and Pooling Layers. This feeds into a Fully Connected Layer which assigns class scores or probabilities, thus classifying the input into the class with the highest probability. Marker-based watershed algorithm is used for segmentation of the image.

Advantages:

● CNN can learn to classify the images directly from raw pixel values without the need for manual feature extraction.

● The proposed system is flexible as it uses CNN which can have multiple convolutional, pooling, and fully connected layers, with varying sizes, depths, and connectivity patterns.

V IMPLEMENTATION

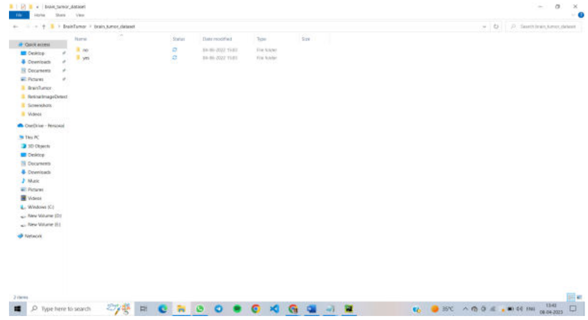
Image Preprocessing: It is very difficult to process an image. Before any image is processed, it is very significant to remove unnecessary items it may hold. After removing unnecessary artifacts, the image can be processed successfully. The initial step of image processing is Image Pre-Processing Pre-processing involves processes like conversion to grayscale image, noise removal and image reconstruction. Conversion to grey scale image is the most common pre-processing practice. After the image is converted to grayscale, then remove excess noise using different filtering methods.

Image Segmentation: Segmentation of images is important as large numbers of images are generated during the scan and it is unlikely for clinical experts to manually divide these images in a reasonable time. Image segmentation refers to segregation of given image into multiple non-overlapping regions. Segmentation represents the image into sets of pixels that are more significant and easier for analysis. It is applied to approximately locate the boundaries or objects in an image and the resulting segments collectively cover the complete image. The segmentation algorithms works on one of the two basic characteristics of image intensity; similarity and discontinuity.

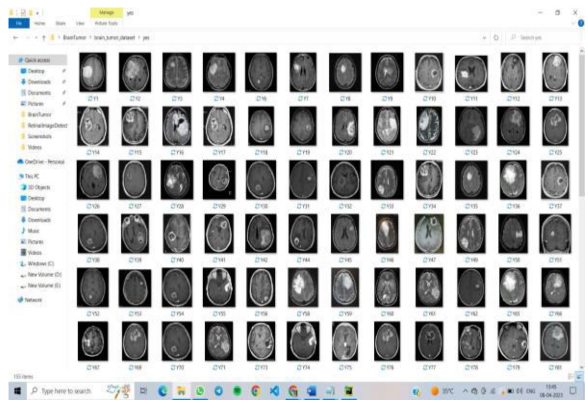
Feature Extraction: extraction Feature extraction is an important step in the construction of any pattern classification and aims at the extraction of the relevant information that characterizes each class. In this process relevant features are extracted from objects/ alphabets to form feature vectors. These feature vectors are then used by classifiers to recognize the input unit with target output unit. It becomes easier for the classifier to classify between different classes by looking at these features as it allows fairly easy to distinguish. Feature extraction is the process to retrieve the most important data from the raw data

Classification: Classification is used to classify each item in a set of data into one of predefined set of classes or groups. In other words, classification is an important technique used widely to differentiate normal and tumor brain images. The data analysis task classification is where a model or classifier is constructed to predict categorical labels. Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data.

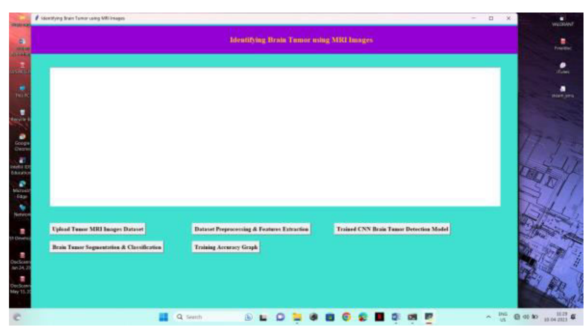
VI RESULTS



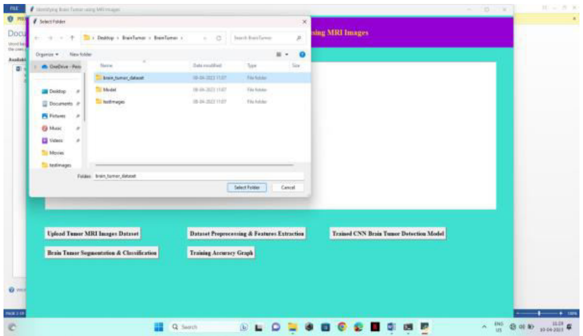
Brain Tumor Dataset



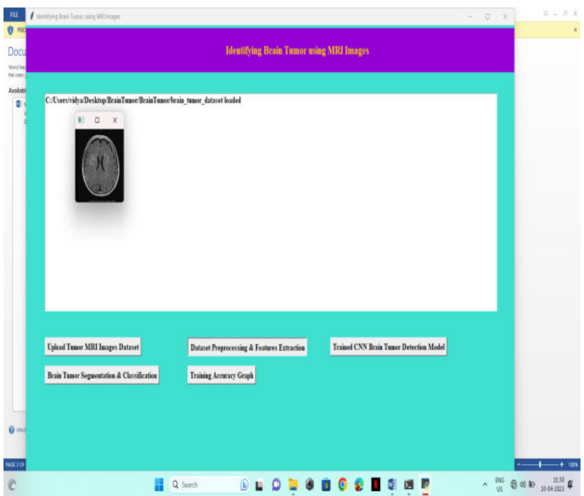
Brain Tumor Images



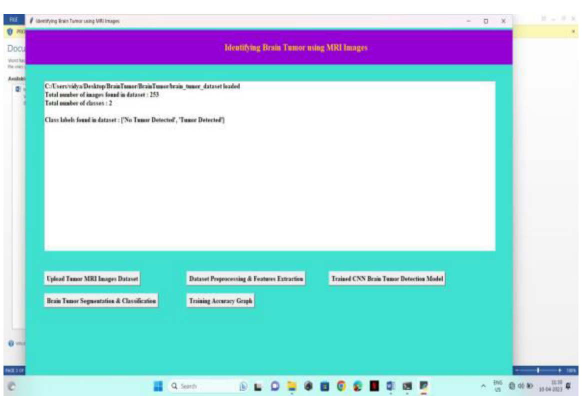
GUI for Brain Tumor Segmentation and Classification



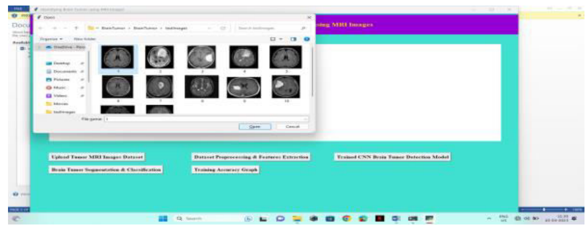
Brain Tumor Dataset Loading



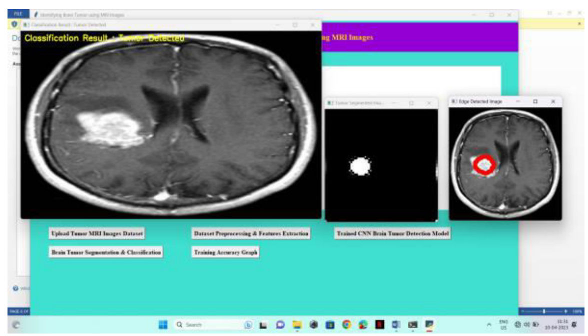
Dataset Preprocessing and Feature extraction



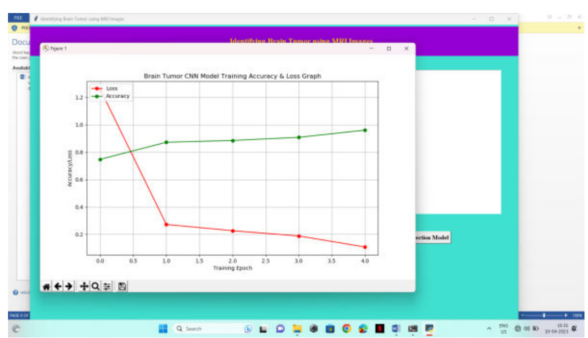
Result of Dataset Preprocessing and Feature extraction



Selecting and Uploading No Tumor Image



Result of Brain Tumor Image Detected



Brain Tumor CNN Model Training Accuracy Graph

VII CONCLUSION

In this paper, we propose automatic brain tumor detection system that identifies brain tumors in brain using deep learning methods. Our proposed deep learning model shows promising results, accurately identifying the presence and precise location of brain tumors in MRI images. The proposed approach achieved better accuracy compared to standard techniques, with a remarkable 96.5% accuracy in our analysis.This paper built on state of the art, analyze and evaluate different medical image segmentation techniques, creating easy to use GUI for medical practitioners to perform automatic segmentation of gliomas

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