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Implementation Paper of Brain Tumor Segmentation using MRI data

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Abstract – *Gliomas are the most frequent primary brain tumors, with varying degrees of aggressiveness, prognosis, and histological sub-regions, such as peritumoral edematous, necrotic core, active, and non-enhancing core. Variable intensity profiles spread throughout multi-parametric magnetic resonance imaging (mpMRI) images illustrate these sub-regions, representing diverse biological features. In longitudinal scans, the amount of resected tumor is also taken into account while evaluating the apparent tumor for possible progression diagnosis. Furthermore, there is growing evidence that accurate segmentation of multiple tumor sub-regions can provide a foundation for quantitative image analysis to predict patient overall survival. Manual segmentation of brain tumor regions is time-consuming and prone to human error, and its accuracy is determined by pathologists' experience. This implementation uses Deep Learning techniques such as CNN (Convolutional Neural Network), ResNet, ResUNet which upon some fine-tuning produce a model which we can use to predict tumor location.*

Keywords – *Brain Tumor, MRI, Machine learning, Deep Learning, Feature extraction, Image Processing*

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I. INTRODUCTION

Although brain tumors are uncommon, they are extremely lethal. Gliomas are the most prevalent type of brain tumor. Low-grade gliomas (LGG) and high-grade gliomas (HGG) are the two types, with the latter being more aggressive and infiltrative. Gliomas are very invasive because they grow swiftly and aggressively invading the central nervous system (CNS). Every year, approximately 18,000 Americans are diagnosed with glioma, according to the US National Cancer Institute, and many of them die within 14 months.

Magnetic resonance imaging (MRI) has long been used in clinical practice to assess the presence of a tumor and its dissemination to other areas, such as the CNS. In comparison to other techniques such as computed tomography (CT) and positron emission tomography (PET), it also provides soft tissue contrast.

Manual segmentation of brain tumors is usually time-consuming and prone to human errors. Furthermore, it takes a large number of pathologists and a huge amount of time to manually segment brain tumors from all the available MRI data. Hence, the reason to implement different machine learning algorithms for the detection and segmentation of brain tumors. The way that the machine learning models work is that they are fed (trained) with manually labeled instances of MRI scans and this trained model is used for the automatic detection and segmentation of brain tumors on the unlabeled instances. Many machine learning algorithms have been used to detect brain-tumor and segment it. The most notable network architecture in machine learning for segmenting tumors is ResNet, and several improved models have already been developed. Other network architectures have also been implemented such as U-Net and its improved model architectures, DeepMedic, etc.

II. MACHINE LEARNING TECHNIQUES

Deep Learning: Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain albeit far from matching its ability allowing it to “learn” from large amounts of data. While a neural network with a single layer can still make approximate predictions, additional hidden layers can help to optimize and refine for accuracy. The main pro of using deep learning technique is they can be instigated on a hefty datasetwhich can contain millions of instances. When it comes to use of images as the dataset, deep learning techniques are widely used.

Convolutional Neural Networks (CNN): A convolutional neural network, is a network architecture for deep learning which learns directly from data, eliminating the need for manual feature extraction. CNNs are particularly useful for finding patterns in images to recognize objects, faces, and scenes. They can also be quite

effective for classifying non-image data such as audio, time series, and signal data.
CNNs are widely used in pattern recognition in images. This will allow us to create a model which will help us to create a model using the parameters we ought to consider.

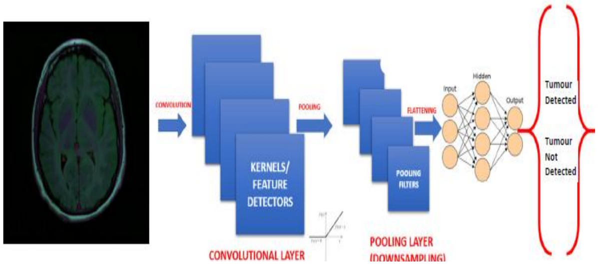

Fig.1. CNN architecture which consists of five layers

ResNet50: Also entitled as Residual Network. This contains 50 because ResNet consists of 50 layers. Proposed by Microsoft research in the year 2015 to solve the problem of vanishing gradient. ResNet uses a system which called as skipping connections. This technique tends to hop the training from some of the layers and tends to connect directly to the output. This model comes in handy for detection of brain tumors in our case.

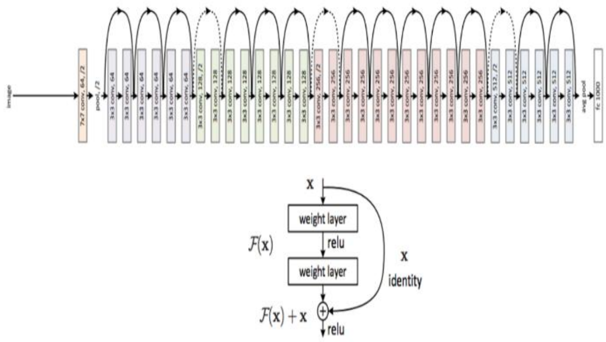

Fig.2. ResNet50 architecture and Skip Connection

ResUNet: ResUNet architecture combines UNet backbone architecture with residual blocks to overcome the vanishing gradients problems present in deep architectures. UNet architecture is based on Fully Convolutional Networks and modified in a way that it performs well on segmentation tasks. ResUNet consists of three parts: Encoder or contracting path, Bottleneck, Decoder or expansive path. This model can be used for brain tumor segmentation part in our case.

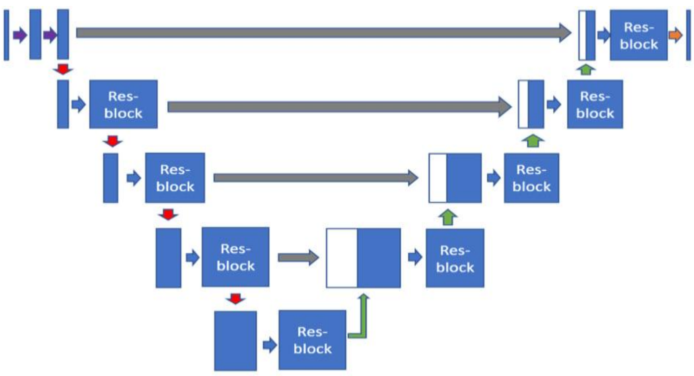

Fig3. ResUNet Architecture

III. SOFTWARE AND LANGUAGES USED

Python: The minute it comes to machine learning python is used. Python does not require an interpreter. Python bargains succinct and comprehensible code. Pythons grammar is clean also the code is decipherable. The straightforwardness of python countenances the developers to code steadfast systems. The developers can devote all their vigor on resolving the glitches of machine learning instead of wasting their time on technical gradations of innumerable languages.

TensorFlow: TensorFlow is an end-to-end open-source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications.

Keras: Keras is the high-level API of TensorFlow. Keras follows best practices for reducing cognitive load: it offers consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear & actionable error messages. It also has extensive documentation and developer guides.

IV. WORKING OF THE PROJECT

Data Collection: It is one of the most important task when it comes to creating a project. We have downloaded the dataset from TCGA (The Cancer Genome Atlas Program) website. The Cancer Genome Atlas (TCGA), is a landmark cancer genomics program, molecularly characterized over 20,000 primary cancer and matched normal samples spanning 33 cancer types.

Data Pre-processing: It is a machine learning technique that powers data to generate original variables that be situated in the training set. Here we use one hot encoding, it is used to assign one hot encoding of labels to train and val dataset. In this stage we also rescale pixel values of the downloaded dataset images.

Transfer learning: Main steps involved are firstly, using feature extraction from pre-trained model and training classification head. Secondly, fine-tuning specific layers of pre-trained base to suit our classification and segmentation tasks.

Training: CNN algorithm is used for training the dataset. The training dataset is the subdivision of the entire dataset which is used to train the model and envisage the results. We train the model for 100 epochs. In this scheme we have used 85% of the data as training data.

Testing: Our model is verified by means of the testing dataset. The testing dataset is engaged to govern how fine the machine can foresee new ripostes supportive of its training. In our project we have used 15% of the dataset asthe testing data.

V. RESULTS

The main goal of this project is to achieve a model which gives us an accuracy in the highest form. We are getting an accuracy of 98.26% while testing the dataset for the brain tumor detection part and 90.41% for the brain tumor segmentation part.

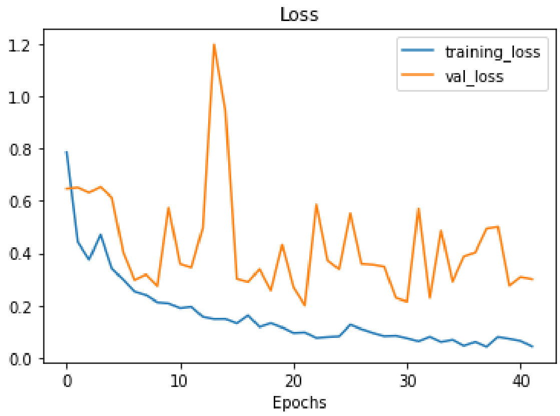

Fig.4a. Plot of training and validation loss and w.r.t epochs (Classification)

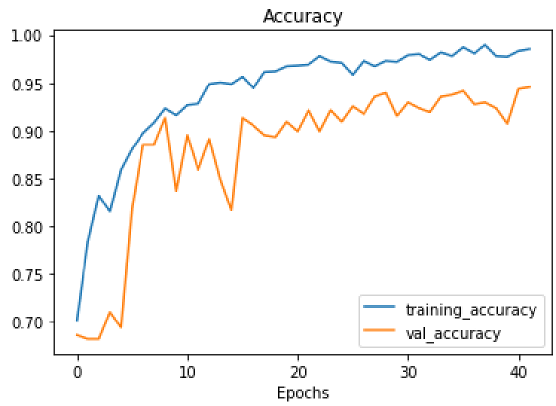

Fig.4b. Plot of training and validation accuracy w.r.t epochs (Classification)

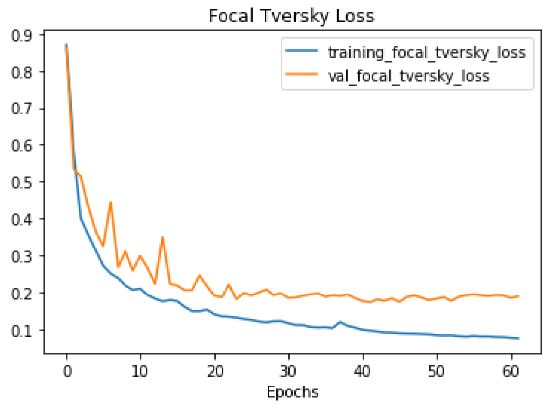

Fig.4b. Plot of training and validation Focal Tversky loss w.r.t epochs (Segmentation)

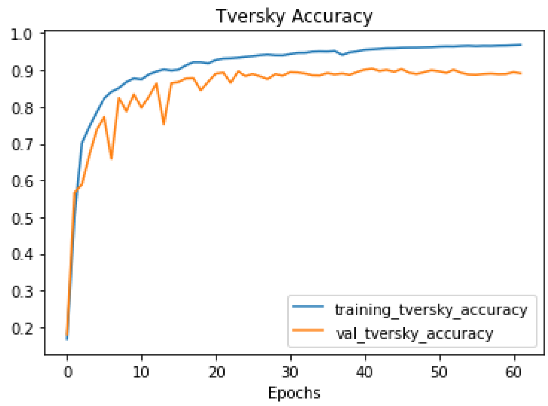

Fig.4b. Plot of training and validation Tversky accuracy w.r.t epochs (Segmentation)

After we have trained the models for both brain tumor detection and segmentation tasks respectively, our final output will be in the form of images which will locate the tumor region in the given MRI scan image.

VI. CONCLUSION

Manual segmentation of brain tumors is usually time-consuming and prone to human errors. Furthermore, it takes a large number of pathologists and a huge amount of time to manually segment brain tumors from all the available MRI data. As a result of this we have createda model which considers MRI data and predicts the results with highest accuracy.

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