



NeuroVision : Brain Tumor Segmentation and 3D Visualization

¹Harsh Bharat Patel, ²Vrunda Hitesh Patel, ³Mihir Kiranbhai Parmar, ⁴Dr. Jitendra Saturwar

¹Student, ²Student, ³Student, ⁴Head of Department (Computer Engineering)

¹Computer Engineering,

¹Universal College of Engineering, Vasai, India

Abstract : Brain tumor segmentation plays a major role in medical image processing. Early diagnosis of brain tumors helps in improving treatment possibilities and increasing the survival rate of the patient. Segmenting brain tumors manually from large volumes of MRI Scans generated in medical routine can be time consuming. This leads to the need for an automatic brain tumor image segmentation system for smooth diagnosis. Brain tumor localization and segmentation from Magnetic Resonance Imaging(MRI) scans are hard and important tasks for several applications in the field of medical analysis. Each brain imaging modality gives unique and key details related to each part of the tumor. Many recent approaches used four modalities namely T1, T1c, T2, and FLAIR. NeuroVision is a flexible and effective Brain Tumor Segmentation and Visualization Web Application. This system uses a CNN-based UNET model for Brain Tumor Segmentation and exhibiting distinct tumor regions. Secondly, Python graphing libraries are used for visualizing different regions of tumors in a 2-D, 3-D, and 360-degree view. A medical report generated includes the tumor's location inside the brain and percent occupancy of the tumor with respect to the brain. Comprehensive experiments are conducted on the BRATS 2020 dataset and show that the proposed model obtains competitive results. The proposed method achieves a mean whole tumor, enhancing tumor, and tumor core dice scores of 88.3%, 75.3%, and 79.0% respectively.

IndexTerms - Brain Tumor, UNET, BRATS, MRI, Segmentation, Visualization, Modalities, Dice Score.

I. INTRODUCTION

A brain tumor is a stage where a set of abnormal cells reproduce in an uncontrolled manner. Magnetic resonance imaging (MRI) is a noninvasive test that is used by doctors to diagnose the medical conditions of a patient. MRI offers images with high resolution and high contrast between soft tissues. MRI provides vital information about shape, size and location of brain tumor for effective diagnosis and treatment plan for the patient. Therefore most of the research in the medical field of brain tumors is done by using MRI images. Various MRI modalities can be created which can be called as weighted images. Such modalities are T1-weighted, T2- weighted, T1c, and Fluid -Attenuated Inversion Recovery(FLAIR). T1- weighted images have high contrast between gray and white matter of brain tissues which is useful for better segmentation of brain tumors. T1-weighted contrast gives enhanced image of T1 and FLAIR makes tumor region hyperintense that's why it is used for brain tumor structure diagnosis.

NEED OF THE STUDY

MRI images represent a crucial and challenging task in diagnosis and treatment planning which are useful for accurate segmentation of brain tumors. Image segmentation is a dynamic field in medical imaging, which consists of extracting one or more tumor regions from the image, which makes the tumorous region interesting for the treatment. To perform brain tumor detection various algorithms have been developed in the literature which includes threshold-based methods, region-based methods, deformable methods, classification methods, and deep learning. But in this work UNET has been used for detection and segmentation of brain tumors. Image Visualization also plays a very vital role in the medical field. This helps to determine the possible outcome of a treatment or surgery. Medical professionals could quite easily communicate with the patients what their problems are and how they will be remedied. So the detection, segmentation, visualization of the brain tumor and how much tumor has occupied a region of the brain in percentage, all this process has been performed on a single platform called NeuroVision.

Extraction of the tumor region from healthy brain tissues and brain tumor detection can be performed by using Brain tumor segmentation. Hence, the tumor can have different size and location, the accurate and effective segmentation of tumors becomes a challenging task. Tumors can have various appearance properties like their structure can be nonrigid and can have a complex shape.

II. LITERATURE SURVEY

In [1], The paper presented by J. Seetha and S. Selvakumar Raja, has used a neural network for the design and implementation part for various subdomains like vector quantization, approximation, data clustering, pattern matching, optimization functions, and classification techniques. Convolution neural networks (CNN) are useful for scaling the image and hence they are used for brain tumor classification. They have used a pre-trained model known as CNN to avoid training the whole model step by step.

In [2], The paper presented by Mircea Gurbin, Mihaela Lascu, and Dan Lascu, has used different wavelet transformations such as continuous wavelet transformation (CWT) & discrete wavelet transformation (DWT) for pre-processing purposes. The major difference between the CWT and DWT is how the scale parameters are discretized. They have calculated for both CWT and DWT contrast, correlation, energy, mean, homogeneity, standard deviation, entropy, RMS, variance, smoothness, kurtosis, skewness, image difference features, and accuracy. OTSU algorithm is used for converting an image into a binary image type based on a threshold value. Now for the data classification part, they have used a support vector machine (SVM). Establishing the best hyperplane for an SVM means the one with the largest margin between the two classes. The result shows that SVMs having the proper sets of training data are able to distinguish between abnormal and normal tumor regions and classify them correctly as benign tumor, malign tumors, or healthy brain.

In [3], The paper presented by Eli Gibsona, Wenqi Li, Carole Sudre, Lucas Fidon, Dzoshkun I. Shakir, Guotai Wang, Zach Eaton-Rosen, Robert Gray, Tom Doel, Yipeng Hu, Tom Whyntie, Parashkev Nachev, Marc Modat, Dean C. Barratta, Sebastien Ourselin, M. Jorge Cardoso, Tom Vercauteren, Here they have developed NiftyNet, an open-source deep-learning platform that uses Deep Learning pipelining for data augmentation, loading, transforming, calculating metrics, etc. It illustrates different applications such as segmenting multi-modal abdominal organs, image regression techniques to calculate CT attenuation maps from brain MRI, generation of simulated ultrasound images for specified anatomical poses, and many more.

In [4], The paper presented by Li Liu, Liang Kuang, and Yunfeng Ji, In this paper they have introduced the Sparse Subspace Clustering (SSC) Algorithm to achieve brain tumor image segmentation. Advantage to using this algorithm is to recover and approximate high-dimensional data using low-dimensional data and to reduce the dimension of high-dimensional data effectively along with retaining the correlation between data. Four different modalities as Flair, T1, T2, and T1ce are used as input. For the evaluation purpose, they have calculated dice, Jaccard, precision, and recall. Now for each different noise ratio, they have calculated the index i.e dice, Jaccard, precision, and recall respectively. After Comparison of segmentation performance of three algorithms such as FCM, SVM, SSC under different noise ratios they have found out that the SSC algorithm is giving good performance.

In [5], The paper presented by Tongxue Zhou, Stephane Canu, Pierre Vera, and Su Ruan, have used a multi-modal segmentation network consisting of feature extraction phase to extract different features from all four modalities and uses Correlation constraint to find a correlation between all the modalities using the extracted features. After that Feature Fusion is used to distinguish the most important features from different source images to highlight regions that are greatly relevant to the target region. Then it is provided to the segmentation model to extract RIO i.e Tumor region.

In [6], The paper presented by Seungwoo Jeong, Da-Woon Heo, and Heung-II Suk, they have used the novel Medical Transformer. It is based on a multi-view approach, a given 3D volume image is split into 2D slices from three planes (sagittal, coronal, axial), and these 2D image slices are then provided to the network as inputs. It then pre-trains a backbone network that consists of a convolutional encoder and a transformer in a self-supervised learning scheme. Then, after going through the pre-trained backbone network, 2D slice features are then recovered by their combinations into 3-Dimensional form representations and finally fed into the prediction network for three medical imaging tasks such as Tumor Segmentation, Brain disease diagnosis using classification, and Brain Age Prediction using Regression techniques.

In [7], The paper presented by Tongxue Zhou, Stephane Canu, Pierre Vera, and Su Ruan, A correlation model is introduced to discover the latent multi-source correlation representation. A fusion strategy based on an attention mechanism with obtained correlation representation is proposed to segment brain tumors in the case of missing modalities.

In [8], The paper presented by Daniel Hähn, Nicolas Rannou P. Ellen Grant Rudolph Pienaar, Slicedrop is a web app used to view the 3D Volumes of MRI images. This platform provides features such as opacity, threshold value as well as colors combination for getting a better view and understanding of the 3D model.

III. PROPOSED SYSTEM

Image classification is the general task of Convolution Neural Network (CNN), where the input is an image and output is a label. But, in biomedical cases, its task is not only to classify whether there is a disease or not but also to locate the area of abnormality. UNet, a CNN based segmentation model, is devoted to solving this problem. This is because it is able to localize the tumor and differentiate between borders of brain tumor's sub regions such as Edema, Core and Enhancing by performing classification on every pixel, due to which the input size and output size are same. Our proposed system i.e NeuroVision, uses the same model for Brain Tumor Segmentation and localizing tumor with its distinct regions. The segmented tumor is visualized with the help of available libraries along with which the location of tumor and its occupancy are calculated mathematically from the 3D MRI volume.

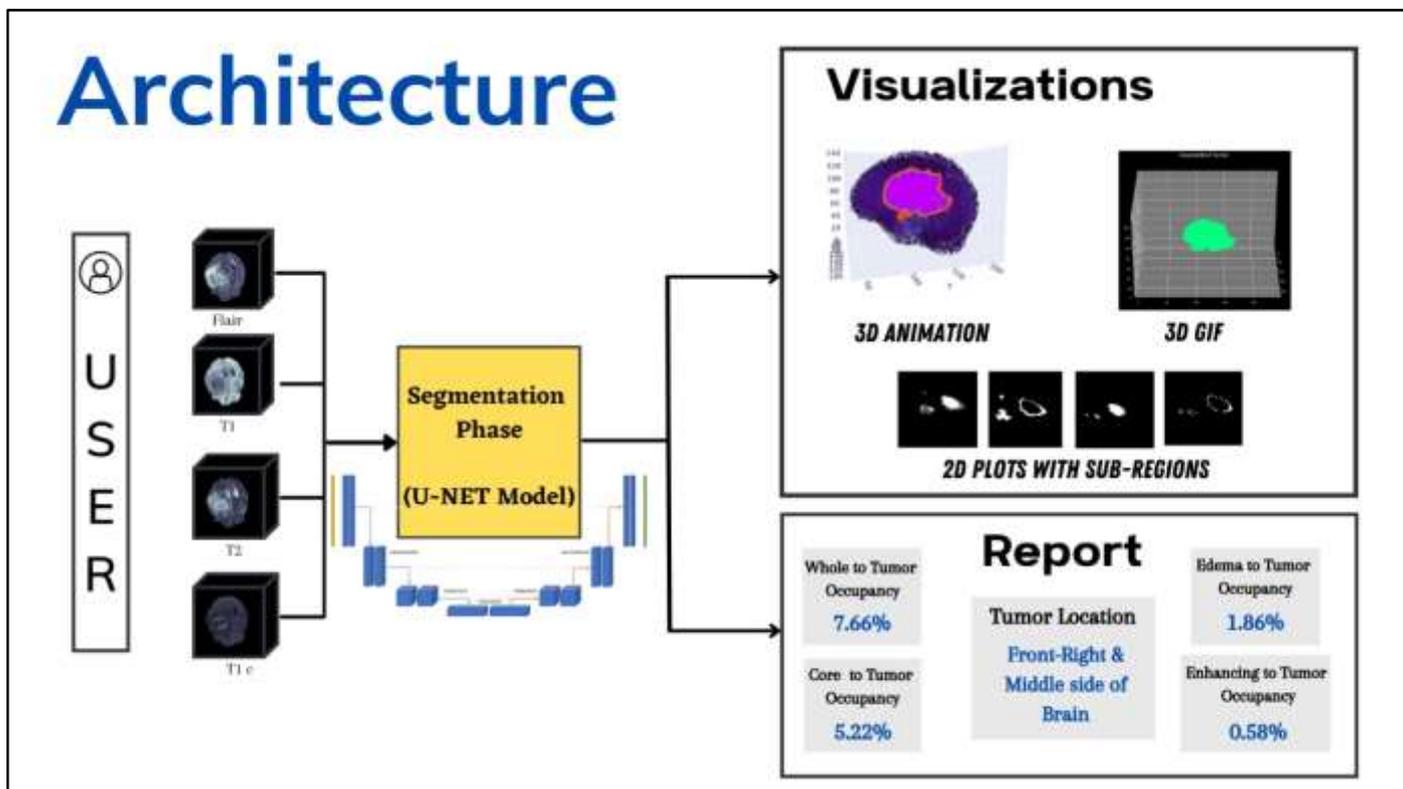


fig. 1 NeuroVision System Architecture

fig. 1 shows the System architecture of NeuroVision. User firstly uploads all the four brain MRI modalities required for tumor segmentation. After which all the four modalities are passed to the U-Net Model for segmentation. The segmented data resulting from the U-Net is stored in the form of a .nii.gz file which is used further for visualization and calculations. The user is then directed to the options page having options to view visualization of segmented tumor in 3D Animated, 2-dimensional plots and 3-dimensional GIF format. The user can view any of the Visualization types as desired. Also, Tumor location and Brain-Tumor occupancy percentage is displayed under the report section.

MODULES

1. Segmentation :

The system takes 4 different inputs of MRI from the user viz. Flair, T1, T2, and T1Ce which are termed as modalities as shown in fig. 2. Flair is a type of MRI scan which has a long inversion time which helps to remove signals from the cerebrospinal fluid(darker) to get the resultant output. T2 image type is similar to FLAIR in which grey matter is brighter than the white matter. T1 and T2 MRI both are produced using TE(Time to Echo) and TR(Repetition Time) times, in which T1 has darker CSF whereas T2 has brighter CSF. Tumor boundaries have higher visibility in T1ce as compared with T1.

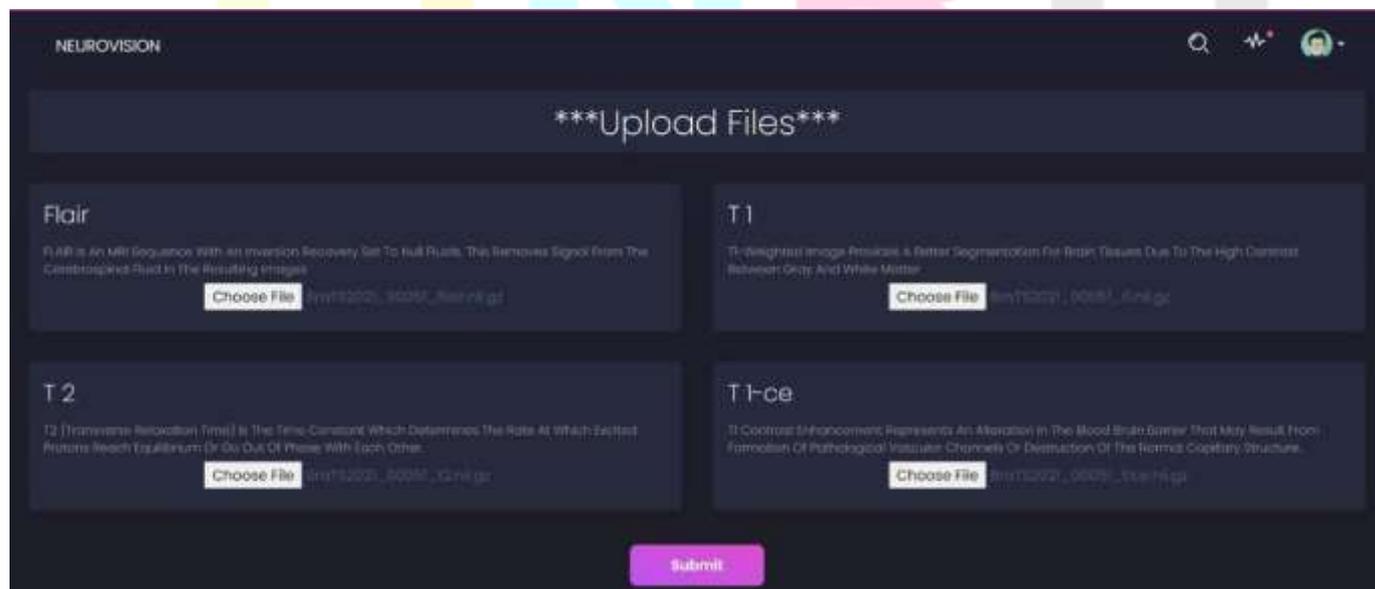


fig 2. Upload modalities section

Data Augmentation such as resizing, cropping and normalization is being performed on all the modalities after which the images are stacked on each other. The Augmented data is then provided to CNN based UNet Model which segments the ROI from the data and will provide the segmented data which consists of the Segmented Tumor Region along with its Sub-regions.

UNET model has following features : in_channels=4, n_classes=3, n_channels=24

‘in_channel’ represents the number of inputs to be given to the model. In this case it has 4 MRI modalities as input. ‘n_classes’ represents how many classes are required in output after segmentation. Over here, it requires 3 classes in output viz. Enhancing part, Edema and Core Part.

2. Visualization :

Visualization consists of two sections viz. 3D and 2D visualization of segmented tumorous regions as shown in fig. 3

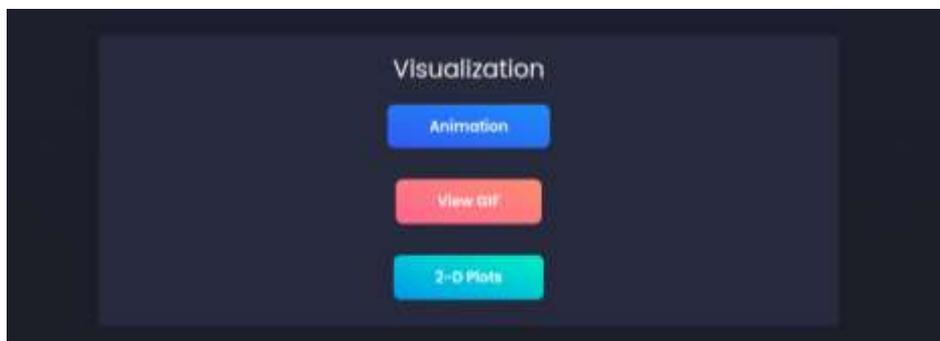


fig 3. Different visualization options

A 3-D animated model is generated by providing the segmented as well as FLAIR MRI data to the ‘plot()’ function of PlotLy Python Library. This 3-Dimensional animated model shows all the three sub regions of tumor along with the brain. GIF file is created by merging all the 2-D images generated from the segmented data from the entire 360 degree area each at 5 degree gap. 2-Dimensional plots of segmented tumor consisting of all regions and individual regions respectively which are generated with the help of inbuilt Python Libraries are displayed to the user.

3. Report Generation:

This module is dependent on the segmentation module as only after segmentation a report can be generated which includes the location of the tumor inside the brain and also the occupancy of tumor with respect to brain along with occupancies of subregions of tumor with respect to entire tumor.

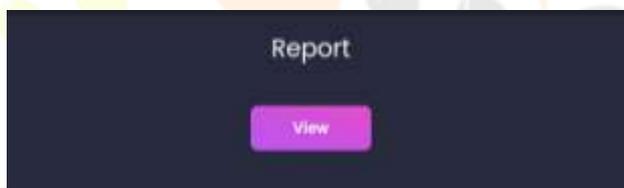


fig. 4 View report option

Tumor location is decided by finding the slice number of the MRI volume containing the maximum number of tumor pixels from all the three axial dimensions i.e Coronal, Axial and Sagittal.

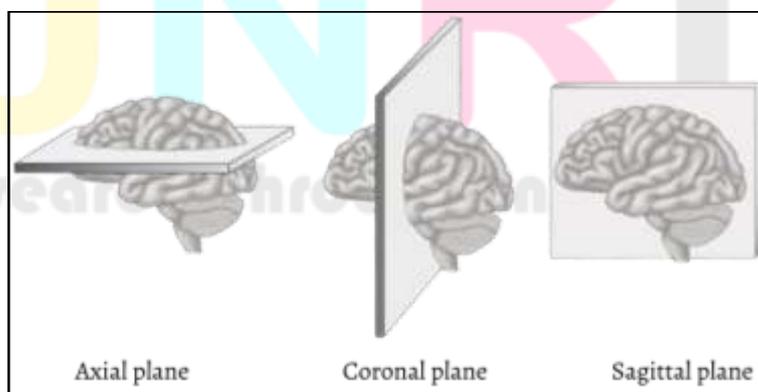


fig.5 Sectional planes of brain

Axial section is a cross-section which will be obtained by slicing through imaging techniques of brain MRI images in a horizontal plane. It is a plane that intersects the longitudinal axis at an angle. The Sagittal plane divides the right and left side of the brain into parts through slices of MRI files. A coronal plane divides the brain into dorsal and ventral(back and front) portions. For division brain slices of MRI files have been used. So in this system to find the location of the tumor density of each slice of each plane is calculated. After calculation those slices are identified with higher density from the planes and are used for providing location for tumors.

Occupancies of tumor are calculated as :

- Tumor-Brain occupancy : $(\text{No. of tumor pixels} \times 100) / (\text{No. pixels of entire brain})$
- Edema-Tumor occupancy : $(\text{No. of edema pixels} \times 100) / (\text{No. pixels of tumor})$
- Enhancing-Tumor occupancy : $(\text{No. of enhancing pixels} \times 100) / (\text{No. pixels of tumor})$
- Core-Tumor occupancy : $(\text{No. of core pixels} \times 100) / (\text{No. pixels of tumor})$

Here, 'No. of Pixel' refers to pixels from the entire MRI brain volume.

IV. RESULTS AND DISCUSSION

Table 1. Performance comparison between different models

Sub-Regions	Segmentation Models/Architectures		
	UNET	Medical Transformer	Latent Correlation Model
Dice WT	88.3	87.33	<u>89.7</u>
Dice TC	<u>79.0</u>	69.69	77.5
Dice ET	<u>75.3</u>	58.82	70.6



fig.6. Dice score comparison for different segmentation models

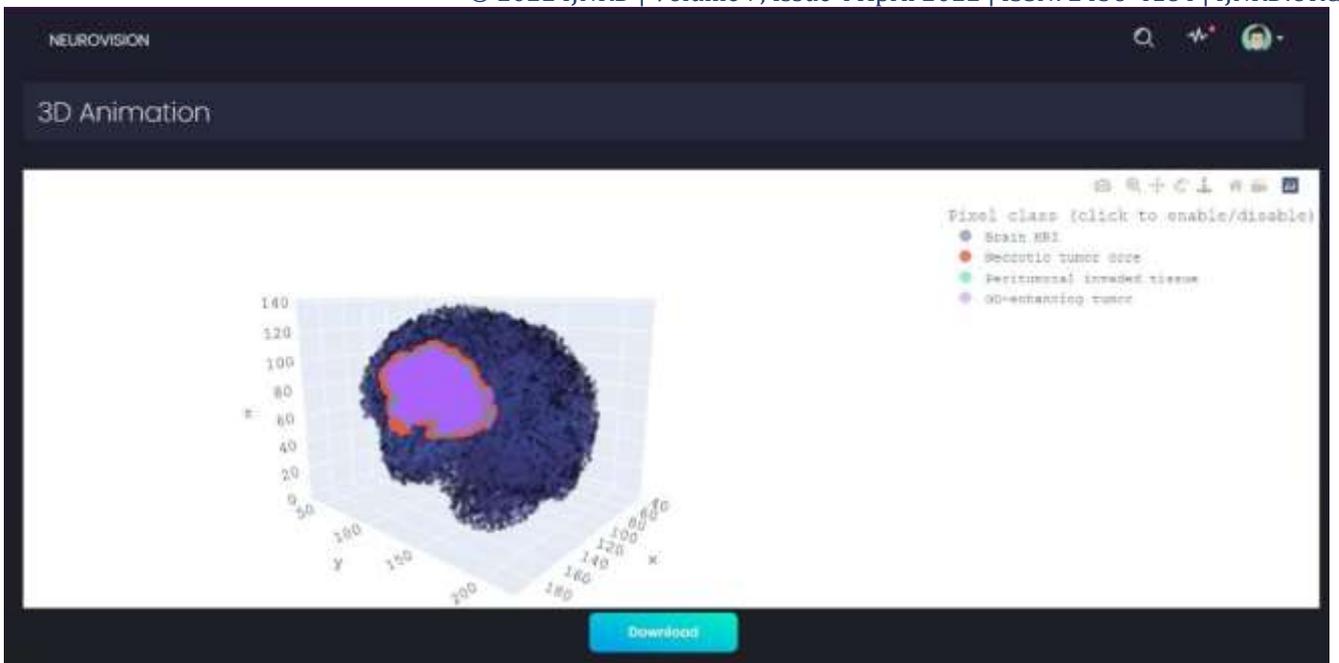


fig.7 Three-D Animation with subregions of tumor

fig. 7. It gives graphical representation of 3 individual different sub-regions in 3 various colors. And the 4th option gives a graphical view which includes all the tumor regions.

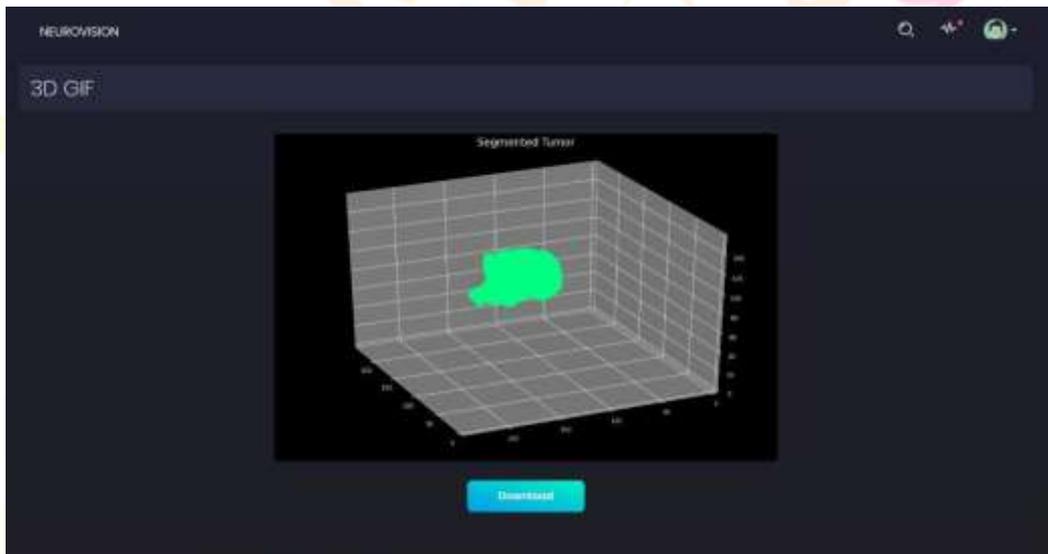


fig.8 3D GIF

fig.8 It gives a 360 degree GIF of segmented tumor in a graphical 3-Dimensional view .

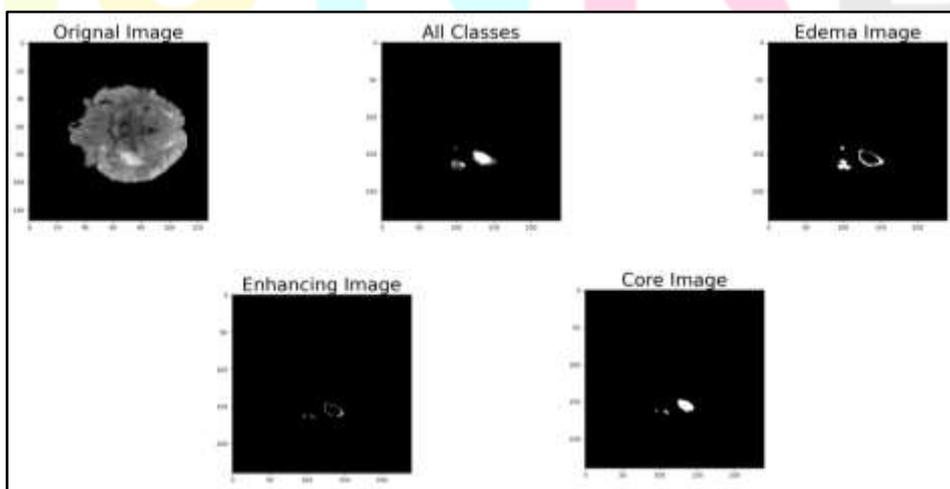


fig. 9 Segmented output in 2-D format

fig.9 Above output provides a 2-Dimensional pictorial view in 5 different images. The 1st image shows original flair data which consists of the whole brain with the tumor. The 2nd image provides all the various classes of the tumor. Next 3 images give visuals of 3 different sub-regions such as Edema, Core and Enhancing respectively.

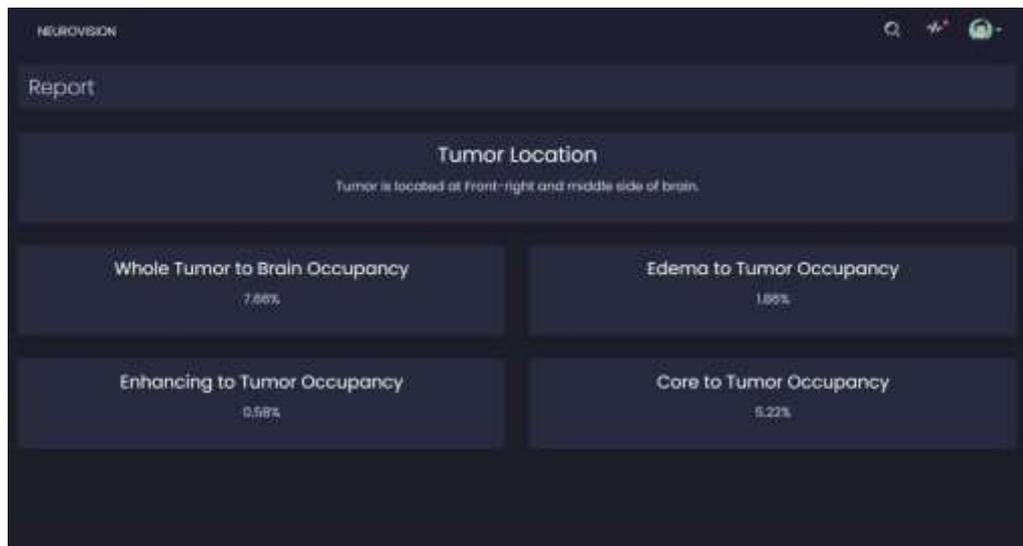


fig.10 Report with tumor location and occupancy

fig.10. This calculative report shows the location of the tumor along with tumor occupancy with respect to the whole brain.

CONCLUSION

In this work, segmentation of the brain tumor is achieved with the help of U-net architecture. BraTS2020 are the datasets used to train the U-net model for the segmentation of brain tumors. While designing the architecture of NeuroVision different models for segmentation purposes like ca-net and U-net were used for experiencing a better result, But U-net was giving great results, and hence it is used. The NeuroVision Architecture has two subsections one is visualization and the other is report generation. Plotly is one of the appropriate visualization tools used to present the tumor regions in 3-Dimensional view. GIF is one of the attractive sections which has a 360-degree rotation of segmented tumor parts. 2-Dimensional view with its sub-region gives a clear idea of Edema, Core and Enhancing part with the download feature. The report section has tumor location along with occupancy of Edema, core and Enhancing part respectively with respect to the whole brain.

REFERENCES

- [1] J. Seetha1 and S. Selvakumar Raja2, (2018), "Brain Tumor Classification Using Convolutional Neural Networks", biorXiv.
- [2] Mircea Gurbin *, Mihaela Lascu †, and Dan Lascu ‡, (2019), "Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines", IEEE.
- [3] Gibson, Eli & Sudre, Carole & Fidon, Lucas & Shakir, Dzoshkun & Wang, Guotai & Eaton-Rosen, Zach & Gray, Robert & Doel, Tom & Hu, Yipeng & Whyntie, Tom & Nachev, Parashkev & Barratt, Dean & Ourselin, Sébastien & Cardoso, Manuel Jorge & Vercauteren, Tom, (2017), "NiftyNet: a deep-learning platform for medical imaging", Computer Methods and Programs in Biomedicine. 158. 10.1016/j.cmpb.2018.01.025.
- [4] Li Liu, 1 Liang Kuang,1,2 and Yunfeng Ji1, (2020), "Multimodal MRI Brain Tumor Image Segmentation Using Sparse Subspace Clustering Algorithm", Hindawi.
- [5] Tongxue Zhou, Stephane Canu, Pierre Vera, and Su Ruan*, (2021), "3D Medical Multimodal Segmentation Network Guided by Multi-source Correlation Constraint", ICPR.
- [6] Seungwoo Jeong, Da-Woon Heo, and Heung-Il Suk, (2021), "Medical Transformer: Universal Brain Encoder for 3D MRI Analysis", IEEE.
- [7] Tongxue Zhou, Stephane Canu, Pierre Vera, and Su Ruan*, (2021), "Latent Correlation Representation Learning for Brain Tumor Segmentation with Missing MRI Modalities", IEEE.
- [8] Daniel Hähn1, 3, Nicolas Rannou P. Ellen Grant Rudolph Pienaar, (2012), "Slice:Drop", IJES.