Brain Tumor Detection and Segmentation using UNET

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Abstract - *Brain tumor detection is one of the most complex biomedical problems. Its anatomical structure makes it complex to cure neuro medical issues. Medical segmentation is a challenging part in curing intense brain tumors. In such scenarios, deep learning algorithms are used to resolve the complexity of segmentation and detect the tumor accurately. The Convolutional Neural Networks (CNN) has been developed by the efficient auto segmentation technology. UNET is used along with methods of computer vision to increase the rate of successfully detecting the tumor. Use of biomedical image segmentation extensively has resulted in high rates of curing the tumor accurately. In this paper, we are proposing a multimodal brain tumor segmentation using 3D UNET. We have used the BraTS 2020 dataset which contains 369 3D MRI images that are used for training while 125 MRI images that are used for testing. We have developed a 3D model which generates the output in 3D format and were able to achieve accuracy of 98.5%.*

Key Words: Brain Tumor, BraTS 2020, CNN, Gliomas, MRI, UNET, Segmentation.

1. INTRODUCTION

Brain cancer treatment requires high expertise and precision as it is one of the most complex procedures in the biomedical field. Deep learning is a class of machine learning. Deep learning algorithms use multiple layers in order to solve complex problems. In this paper, we have used methods like CNN: UNET to perform segmentation over the tumor affected area of the brain. The main problem of detecting a brain tumor is its area of infection as well as the intensity. Hence, brain tumor segmentation is done. For image segmentation, the method of image inpainting is used. Image inpainting is a method done prior to UNET in order to enhance the image quality. It helps to smoothen the image. This helps in identifying the tumor more accurately with the help of similarity index. Using the 3D MRI images given in the dataset, we have imported them to the system to perform UNET and perform segmentation to acquire the accurate tumor present in the brain. Mathematical models such as Edge-Based Detection Method, Rough Set-Based Fuzzy Clustering and Cross-Entropy Loss Function. With the help of these models, segmentation is done precisely.

2. LITERATURE REVIEW

Various researches clearly depict the importance of deep learning methods for learning and identifying specific patterns for accurate characterization of a specific problem. In the Recent study performed by Ling Tan and Wenjie Ma [1] within the context of medical image segmentation in the year 2021 they have proposed a multimodal brain tumor image segmentation method based on ACU-Net network using different volumes of dataset such as BraTS 2015, BraTS 2018, BraTS 2019. This study definitely showed an increased dice, recall, precision and can employ an active contour model to overcome image noise and edge slits to better identify low-contrast and low-resolution in the image but This study is also presented with poor adaptability.

As we know that gliomas are malignant and heterogeneous Mahnoor Ali,Asim Waris proposed an ensemble of two segmentation networks 3D CNN and a U-net [2] which helps us for better and accurate predictions. In this study researchers used BraTS 2019 challenge dataset and achieved a good dice score of 0.91 for whole tumor region and provided efficient and robust tumor segmentation across multiple regions. There were certain discrepancies and deficiency as the recognition rate was only 83.4% hence better pre and post processing of data was required.

The most formal and important step for brain tumor segmentation is to detect the boundary of the tumor i.e., edge detection. A group of researchers named Ahmed H. Abdel-Gawad, Lobna A. Said proposed a System for Optimized edge detection in case of brain tumor detection by analyzing MRI images [3]. It uses different Techniques and Algorithms such as Balance contrast Enhancement Technique (BCET), skull stripping and Genetic Algorithm (GA) which comes under evolutionary sciences.

For proper diagnosis and planning for brain cancer treatment proper brain tumor segmentation is very important so in the year 2020 certain researchers named Nagwa M. Aboelenein, Piao Songhao, Alam Noor proposed an architecture called Hybrid Two Track U-net (HTTU) which is used for Automatic Brain Tumor Segmentation [4]. It uses different methods such as N4ITK Bias Correction, Focal loss and Generalized dice score functions. It uses BraTS 2018 dataset and also achieved 0.865 dice score for whole tumor but it could not identify the underlying layers of the images used.

By using feature fusion on several levels we can make full use of hierarchical features to reveal the importance of refinement and aggregation of features in brain tumor segmentation.Dongyuan Wu,Yi Ding,Mingfeng Zeng [5] developed a Multi Features Refinement and Aggregation

(MRA) Model for improvement of segmentation accuracy. It uses BraTS 2015 dataset and achieves 0.83 dice score for whole tumor but has poor performance in case of enhancing tumor.

Yibo Han and Zheng Zhang developed an Image Interactive framework for Brain Image Segmentation [6] which is assisted by Deep Learning concepts. It uses Deep Convolutional Neural Networks (DCNN) which is a Multi-Task Deep Learning Approach (MTDLA) but it produces minor mistakes due to unsupervised fine tuning.

During Brain Tumor Segmentation based on MRI Modalities certain noisy regions affect the accuracy and performance greatly. Guohua Cheng and Hongli Ji developed an system which is used to evaluate Adversarial Perturbation based on MRI Modalities [7] but when four modalities are attacked or damaged we will observe a severe degradation of performance and accuracy will occur.

To improve the performance of medical image segmentation and enhancement of local feature extraction Jianxin Zhang, Zongkang developed an Attention Gate ResU-net model for Automatic Brain Tumor Segmentation [8]. They used different dataset volumes such as BraTS 2017,2018 and 2019. It surely outperform baselines of U-net and ResU-net but loses an amount of context and local details among different slices.

For proper extraction of Image features in brain tumor segmentation Weiguang Wang,Fanlong Bu developed an explanatory model which combines Learning Methods of CNN with feature extraction of Images in Brain Tumor detection [9]. It is used for performance analysis, diagnostic reports and as theoretical references for any related research. Dataset used is GBM data volumes and it achieves 0.872 dice score for whole tumor but has high computational time and complexity.

For better Supervision and Excitation function Ping Liu, Qi Dou, Qiong Wang developed an Encoder-Decoder Neural Network [10] containing 3D Squeeze and Excitation and also including Deep Supervision for Brain Tumor Segmentation. They used BraTS 2017 dataset and N4BiasFieldCorrection algorithm along with V-net (DSSE-V-net). Certain drawbacks were found such as limited size kernel and receptive field problem.

There are various types of neural networks which can be used for Brain Tumor Segmentation, Wu Deng, Qinke Shi proposed a Deep Learning based model for brain tumor segmentation which uses two neural networks Heterogeneous Convolutional Neural Networks (H-CNN) and CRF-Recurrent Regression based Neural Network (RNN) [11]. It uses the BraTS 2017 dataset for evaluation and achieves high accuracy and recognition rate.

Tamjid Imtiaz, Shahriar Rifat developed an Automated Brain Tumor Segmentation system which is based on Multi- Planar Superpixel Level Feature Extraction [12]. To reduce the bias in intensities an Intensity Adjustment Scheme is applied on the whole 3D MRI images. Extremely Randomized Trees are used for classification of tumor and non-tumor classes. This study uses NCI-MICCAI 2013 challenge dataset with certain drawbacks found such as low level of precision in the tumor region segmentation.

As most medical imaging dataset which are used for brain tumor segmentation are small and fragmented Changhee Han, Leonardo Rundo, Rhyosuke Araki developed a system as Brain Tumor Augmentation for Tumor detection which is achieved by combining Noise-to-Image and Image-to-Image GAN [13]. It uses BraTS 2016 dataset with ResNet-50 and t-SNE methods but results in poor optimization results.

The classification of brain cancer by manual method requires the knowledge and expertise of a Physician who is experienced enough in the medical field. Abdu Gumaei, Mohammad Mehedi Hassan came up with a Hybrid Feature Extraction Method for Brain Tumor Segmentation that includes implementation of Regularized Extreme Learning Machine (RELM) [14]. BraTS 2013 dataset, Fuzzy C-means algorithm and Cellular Automata with a Grey Level Co-occurrence matrix (GLCM) are used in this study and relatively low efficiency is present.

Cascading is a very popular concept in neural networks classes. Kai Hu, Qinghai Gan, Yuan Zhang developed a system for brain tumor segmentation which uses Multi- Cascaded Convolutional Neural Networks (MC CNN) and Conditional Random Field (CRF) for its implementation [15]. When integrating into 3D CNN Poor effectiveness of images is observed.

Out of the multiple imaging techniques used to detect brain tumors MRI is commonly used as it has superior image quality with highest resolutions are obtained without any radiation. In the year 2019, Hossam H. Sultan, Nancy M. Salem, Walid AL-Atabany proposed a Deep Learning model which is based on multi-classification method for Brain Tumor Images [16]. It uses Nanfang Hospital and General Hospital and The Cancer Imaging Archive (TCIA) public access repository for evaluation of the proposed model.

Aimin Yang, Xiolei Yang, Wenrui Wu did a research study in the year 2019 based on Feature Extraction of Tumor Image using Convolutional Neural Networks (CNN) [17] which concluded that CNN algorithm shows high accuracy in tumor image feature extraction and also demonstrated different advantages of CNN in neuroimaging field. In this study local binary model algorithm and convolutional neural network algorithm are used to extract the required features of tumor.

In recent years the applications of AI in Magnetic Resonance Imaging (MRI) have been applied in various biomedical studies. In the year 2018 Gunasekaran Manogaran, P. Mohamed Shakeel developed a Machine Learning Based Approach for Brain Tumor Detection and data sample imbalance analysis [18]. It contains an improved orthogonal gamma distribution-based method which is used to analyze the under-segments and over-segments of brain tumor regions to automatically detect abnormalities in the Region of Interest (ROI) but it has low real-time applications.

In the neuroscience field, different Algorithms are used for precise and accurate brain tumor Segmentation. Qingneng Li, Zhifan Gao proposed a Unified Algorithm for Glioma Segmentation using Multimodal MRI images [19]. It uses a Two Step Refinement Strategy to maintain PPV values which in turn increases processing time and reduces the recognition rate.

Guotai Wang, Wenqi Li, Maria A. Zuluaga developed an Interactive Medical Image Segmentation model with the help of Image-Specific Fine Tuning [20]. This model uses Pre-trained Gaussian Mixture Model (GMM) so it has fewer user interactions and less user time than traditional interactive segmentation methods. But this model requires a large number of annotated images for training.

1.1 ABBREVIATIONS AND ACRONYMS

CNN (Convolutional Neural Network), BraTS (Brain Tumor Segmentation), MRI (Magnetic Resonance Imaging), CRF (Conditional Random Fields), GAN (Generative Adversarial Networks), PPV (Positive Predictive Value).

3. LIVE SURVEY

The survey discussed here aims for the live impact of other methodologies in Brain Tumor segmentation earlier. In this survey, hospitals which are currently working on detection and segmentation of Brain Tumor based on this particular method gives us a clear idea about the procedure and overall desired results acquired during their process.

In order to identify the sub-regions such as Edema, enhancing tumor, and Necrosis this Tata Memorial Hospital proposed a 3D UNET architecture which helped in identifying these radiological sub-regions of a Brain Tumor. To keep the balance between the tumor and non-tumor patches inside a brain, patch extraction scheme has also been put forward to address the problem. And along with which the architecture helps for precise location of a Tumor by using symmetric expanding features and to capture the context by contracting path. The desired results achieved during the process contains the Dice Scores of 0.92, 0.90 and 0.81 for Whole Tumor (WT), Tumor Core (TC) and Enhancing Tumor (ET), respectively based on independent patients' dataset from the hospital.

Present work in Apollo Hospital gives insight about a visual and quantitative analysis on automated Brain Tumor segmentation using Fuzzy-Possibilistic C-Means (FPCM) methodology. The K-means w.r.t patch-based technique is also used to carry out the skull scripting, along with Region of Interest (ROI) it is possible to measure the quantity of the exact region of a brain tumor located. The results involved are improved based on performance achieved than the previous algorithms used to carry out the same benchmark results.

4. DATASET DETAILS

4.1 PREPARATION

The dataset used for our system is BraTS2020 Dataset (Training + Validation). It contains Multi-Magnetic Resonance Imaging (MRI) scans. The Dataset mainly focuses on the segmentation of an essential heterogeneous brain tumor, namely gliomas. It is also used to evaluate the uncertainty between different algorithms in tumor segmentation.

- ✓ Dataset Reference - www.kaggle.com
- ✓ Size - 40GB
- ✓ No. of Training Sets - 369
- ✓ No. of Validation Sets – 125

4.2 PREPROCESSING

Before loading the dataset into the training model, we have to perform data pre-processing operations to remove noisy regions and extract key characteristics required for the segmentation. BraTS 2020 does not contain any missing values or set of MRI images for any patient and all the data fields are well labelled. The dataset is split into two parts: Training and Testing for further evaluation.

5. PROPOSED WORK

With the survey done above there are certain remarkable discrepancies and inefficiencies with regards to the segmentation accuracy which found to be low due to lack of efficient algorithms. Pre-processing of the data is not done due to which the dataset might contain noisy regions and erroneous values in-turn affecting the accuracy and recognition rate. Along with which boundary and depth detection of tumors is not accurate which makes it difficult to perform necessary actions. Also, the process is semi-automated with a low performance index that involves manual work. Thus, poor results obtained with regards to the enhancing tumor region. Our proposed system overcomes certain problems identified in the previous work. With this proposed system, we aim to increase the accuracy of the Brain Tumor segmentation by using a better training set and algorithmic patterns for the Whole Core (WC) and Enhancing tumor region. Projecting the Tumor region is segmented in 3D format for better understanding of underlying layers, depth, location, size and length. Also, better preprocessing and post-processing of data has been done for efficient output.

5.1 SYSTEM ARCHITECTURE

After the completion of Requirement gathering and Requirement Analysis, we arrive at the design stage of our implementation. The System Architecture represents the overall functionalities, modules, process flow, and a brief overview of the complete system through the eyes of a developer. Different modules have different assigned functionalities which are implemented in a defined manner with supervised control flow. In our proposed system we have converted the tumor detection operation into small modules which increases modularity and also strikes out various interdependencies present in case of simultaneous execution. Fig. 1 shows the System architecture of our System.

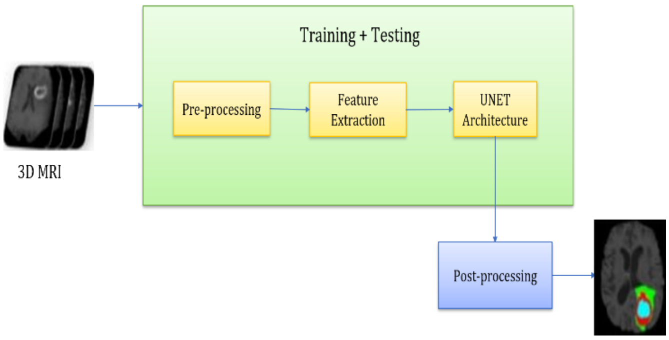

Fig. 1 – System Architecture

The dataset used contains a set of 3D MRI images of every individual patient which are used as input for our system. The main functional block is named as "Training + Testing" which contains different operational modules which are interlinked and follows a sequential pattern for its implementation. First sub-module is used for Data Preprocessing which includes operations such as Data cleaning, Data Transformation etc. The next module followed by Data preprocessing is Feature Extraction, it contains different operations such as skull stripping, boundary detection algorithms, cluster analysis, intensity, slicing methods etc. which are used for accurate delineation of Gliomas. After the completion of the first two sub- processes, we provide the outcome as input images to the U- net Architecture which contains a defined set of convolutional layer information and algorithmic conditions specified for segmentation. The outcome received after execution of the "Training + Testing" functional block we provide this as an input for Data Post-processing which provides us only the segmented portion of brain tumor as an output.

5.2 UNET ARCHITECTURE

U-Net is an advanced version of a sophisticated convolutional neural network (CNN) that was specially developed for biomedical image segmentation. The feature about U-Net which differs from CNN is that the target is not only to classify whether there is an infection or not but also to identify the area of infection. U-Net yields more precise segmentation by using comparatively fewer high-resolution images than previously used FCN (Fully Convolutional Networks) and other segmentation models. It also does not require multiple runs and a labelled set of images for segmentation. U-Net is divided into three main layers namely, Contraction Path, Bottleneck and Expansion Path. In order to work on fewer parameters Max Pooling operation is carried out which reduces the size of the feature map. In this process, the popular activation function ReLU (Rectified Linear Activation Function) has been used which outputs the positive input directly but outputs zero if the input is negative.

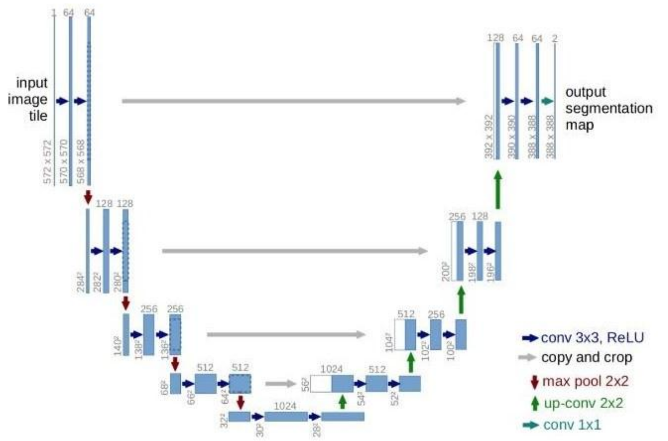

Fig. 2 – UNET Architecture

5.3 MATH

For implementation of any algorithmic model certain mathematical constraints must be satisfied to ensure proper structure and provide strong calculative measures for productive assessment and evaluation of outcomes received.

5.3.1 EDGE BASED DETECTION METHOD

Edge based detection itself includes multiple mathematical methods that identify the coordinate pixels of an MRI scan at which the image brightness might show some discontinuities. The pixels at which the brightness changes sharply are clustered into a set of curved line segments called edges. In case of Brain Tumor Segmentation, we can drastically improve the performance of any neural network applied if we first detect the boundary of the whole tumor region instead of applying the network on a complete MRI image. If we apply U-net architecture on a complete brain MRI image then the processing time will be considerably high, the recognition rate will be very low due to the saturation in the convolutional layers after repetitive scans.

$$argmin_u \, \gamma \|\square_u\|_0 + \int (u+f)^2 \; dx$$

...Eq. 1

$$\frac{1}{\sigma(\ell_i)\sqrt{2\pi}} e^{-(f_i-\mu(\ell_i)^2/(2\sigma(\ell_i)^2)} d\ell_i$$

...Eq. 2

$$f(x) = \frac{I_r - I_\ell}{2}\left(\text{erf}\left(\frac{x}{\sqrt{2}\sigma}\right) + 1\right) + I_\ell$$

...Eq. 3

5.3.2 ROUGH SET-BASED FUZZY CLUSTERING

A rough set-based fuzzy clustering consists of two steps, initial clustering based on rough set and secondary clustering based on fuzzy equivalence relations. The RSFCL algorithm has preferable clustering validity and high run efficiency in handling the clustering problems of both numerical data and nominal data. In case of Brain Tumor Segmentation after successfully detecting the tumor boundary by using edge-based detection method, we use rough set to locate pixels which are included in the isolated region formed after Edge detection and Fuzzy Clustering to form clusters of pixels on the basis of similarity in intensity variation. This clustered set of pixels also resides in the region confined inside the tumor boundary.

$$r(C_i, C_j) = \frac{\sum_{s=1}^{n_k} \delta_s}{n_k + n_l - \sum_{s=1}^{n_k} \delta_s}$$

...Eq. 4

5.3.3 CROSS-ENTROPY LOSS FUNCTION

Cross entropy loss is also called logarithmic loss or log loss, it is used along with U-net Architecture to minimize the loss occurred during training. Cross entropy is the most commonly used loss function in machine learning as it measures the performance of a classification model by considering output as a probability value between 0 and 1.

$$H\ (p, q) = -\ E_p\ [log\ q]$$

...Eq. 5

$$H(p,q) := \sum_i p_i \log q_i$$

...Eq. 6

6. RESULTS AND DISCUSSION

6.1 RESULTS

In our proposed system, we have successfully extracted the segmented brain tumor images. We adopted the method of UNET to extract the segmented tumor in the format of two-dimensional (2D) as well as three-dimensional (3D). The base architecture used is the same for both methods 2D & 3D. In this section working functionalities, evaluation metrics, performance scores, graphical representation of trends in case of parameters used are shown in a detailed manner. To measure the segmentation effect of UNET, this paper adopts subjective visual evaluation as well as manual calculations to judge the experimental results. The results section will be divided in two parts for precise articulation of outputs achieved for our system.

6.1.1 2D EVALUATION

6.1.1.1 MATERIALS AND METHODS

In our system we have used Python 3.7 as the programming language throughout the modules as it provides a vast support of libraries and also increases productivity. For training the deep learning model we have used keras as a backend with TensorFlow support. Keras contain various layers which are basic building blocks of neural networks. From layers certain functionalities are imported such as Batch Normalization, Activation function and Convolution etc. Adam optimizer is used for the training model as it is the most efficient optimizer in case of convolutionary operations. For fitting the training model, the batch size is kept as 32 and epoch are set to 40. After the completion of training, we save the weights of the trained model in HDF5 (.h5) format for further evaluation.

6.1.1.2 OUTPUTS AND PERFORMANCE SCORES

With the proposed architecture, the segmented tumor is extracted in the form of 2D images. Fig. 3 shows the image of tumor extracted.

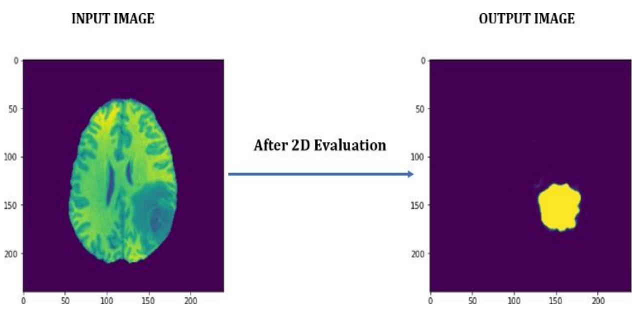

Fig. 3 – 2D Output

- **Recognition Rate (Sensitivity/Recall):** It is defined as a measure on how well a system can identify true positive values. It is also named as TRUE POSITIVE VALUE. Our system has achieved a recognition rate of 96.13 %.

$$Sensitivity = \frac{TP}{TP + FN}$$

...Eq. 7

- **Specificity:** Specificity is the measure of finding the proportion of actual negative values which are predicted negative. Hence, it is also called TRUE NEGATIVE VALUE. The specificity produced for the proposed system is 99.91 %.

$$Specificity = \frac{TN}{TN + FP}$$

...Eq. 8

- **Precision:** Precision is the ratio between the True positive and all the positives. Amount of precision recorded is 92.30 %.

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

...Eq. 9

- **Accuracy:** Accuracy is defined as the number of correctly predicted values from all the data values. The overall accuracy for the proposed system is measured as 99.10 %.

Fig. 4 shows the constant and minimal increase in accuracy over every subsequent epoch cycle.

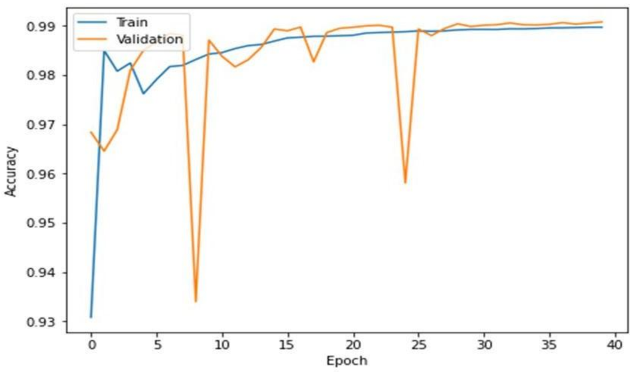

Fig. 4 – Accuracy vs. Epoch

6.1.2 3D EVALUATION

6.1.2.1 MATERIALS AND METHODS

For implementation of the model proposed which generates the output result of segmented tumor in 3D format there are certain prerequisites that we have to fulfill before jumping into the coding stage. These prerequisites can be categorized as software requirements and hardware requirements depending upon the platform used for implementation. In case of Deep learning models, a strong processor capable of complex computation is required to reduce the processing time and increase the efficiency along with accuracy. In the general scenario, GPUs with CUDA enabled processors are used for training of neural networks and machine learning models. Certain computations can be performed on CPU with moderate RAM before training the model. The hyperparameters can be manipulated for various runs to capture different behavior of the model as training the model to achieve high accuracy and precision may require trial and run again approach before, we overfit or underfit the model. When it comes to software requirements and specification the compatibility and supportability of programming language along with IDE used is very important. Also, if someone desires to train a particular neural model on GPU for better performance then CUDA compatibility and support for present NVIDIA drivers must be checked and verified before getting into any further processes. Nowadays there are various options to integrate our system on a cloud-based architecture which diminishes high computational hardware requirements completely.

In 3D evaluation, we have used Python 3.6.3 language for programming for individual components. Also, for neural networks we have used PyTorch, Keras backend with TensorFlow support etc. We have created a simple GUI for better user interaction, in which the user is able to navigate tabs such as Browsing the Input Image file of any individual from the dataset and segment it to obtain the tumor result, accordingly, the segmented tumor in 2D can be converted into a 3D structure with the help of the other tab mentioned 7 below and finally, by clicking the last tab that says "Show Result" gives the output of a 3D Tumor which can be seen from a Bird's-Eye view.

6.1.2.2 OUTPUTS AND PERFORMANCE SCORES

After successfully evaluating the 3D model the output obtained from input 3D MRI are also represented in 3D format. Based on the intermediate snapshots generated for different planes after the evaluation of the model, the most stable plane is selected to display the tumor segmentation which is shown in Fig. 5.

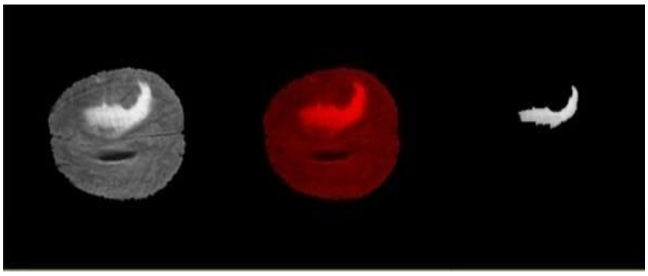

Fig. 5 – Tumor Segmentation

To represent the generated tumor segmentation Fig. 5, in 3D format we convert the stored information about gradual planes and display it in Bird's-Eye view form. Fig. 7 clearly depicts the desired output of an isolated tumor region in 3D. The 3D output generated can be stored on the local device in GIF or MP4 format to further utilize it for any biomedical study based on brain tumor segmentation.

After successfully training the model certain parameters are generated which are also known as performance scores. Some of the parameters with high significance are Dice coefficient (DSC), Recognition Rate (Sensitivity/Recall), Specificity and Accuracy.

DSC also known as F1 Score is 0.579 along with the Recognition Rate of 0.9106 and Specificity as 0.9857 for our proposed system. After the complete evaluation the ACC attained is 98.48%

$$F1\ Score = \frac{2TP}{2TP + FP + FN}$$

...Eq. 10

$$Sensitivity = \frac{TP}{TP + FN}$$

...Eq. 11

$$Specificity = \frac{TN}{TN + FP}$$

...Eq. 12

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

...Eq. 13

Fig. 6 – Accuracy Graph

The Fig. 6 gives us visual representation of Accuracy varying over subsequent epochs.

Fig. 7 – 3D Output

6.1.2.3 CLASSIFICATION METRICS

A Confusion matrix which is also known as error matrix is a table that is often used to describe the performance of a classification model, here, the classification is between tumor pixels and non-tumor pixels classes. Confusion matrix 8 is a special type of contingency table that contains two dimensions actual and predicted values which gives an identical set of classes known as TP (True Positive), FP (False Positive), TN (True Negative) and FN (False Negative). These values summarize the results of our classification and can also be used to derive other performance parameters either through manual calculation or fetching the results to another model.

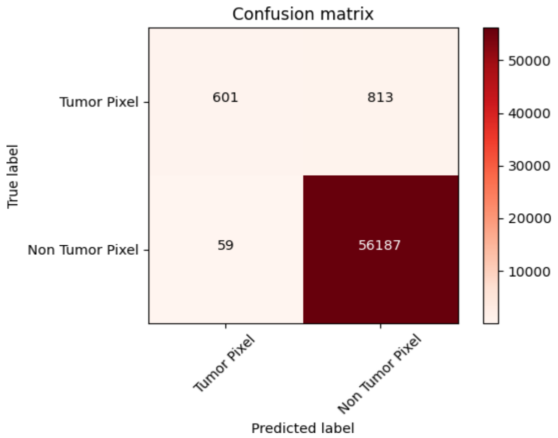

Fig. 8 – Confusion Matrix

Fig. 8 represents the values of identical set of classes generated for our system.

TP = 601	FP = 813
FN = 59	TN = 56187

Using these values, we have calculated other performance parameters such as NPV (Negative Predictive Value), FNR (False Negative Rate), FPR (False Positive Rate), FDR (False Discovery Rate), FOR (False Omission rate), MCC (Matthews Correlation Coefficient).

$$NPV = \frac{TN}{TN + FN}$$

...Eq. 14

$$FNR = \frac{FN}{FN + TP}$$

...Eq. 15

$$FPR = \frac{FP}{FP + TN}$$

...Eq. 16

$$FDR = \frac{FP}{FP + TP}$$

...Eq. 17

$$FOR = \frac{FN}{FN + TN}$$

...Eq. 18

As a result, the performance parameters NPV, FNR, FPR, FDR, FOR, MCC obtained with the help of set of classes generated for the system are 0.9989, 0.0893, 0.0142, 0.5749, 0.0010, 0.6164 respectively.

7. CONCLUSION

In this paper, we have successfully implemented U-Net Architecture for precise and accurate brain tumor segmentation. The algorithm takes various training images provided in BraTS 2020 dataset and uses its predefined convolutional patterns to determine the tumor region effectively. Different mathematical models and strategies such as Edge based detection method (EBD), Rough set-based Fuzzy Clustering, Cross Entropy Loss are applied in an abstract way for calculated process flow and operations. We aim to accurately extract key features and characteristics for the brain tumor by proposing this multimodal brain tumor detection and segmentation system. By this system, we developed a model to represent the whole overview of the brain tumor region. Experimental results prove that our system has a high ACC of 99.10% in case of 2D evaluation and 98.48% for 3D evaluation.

8. FUTURE SCOPE

With regards to the future scope of our proposed system, we aim to obtain the severity of Brain Tumor along with the type of Tumor. Recognition of Survival Rates will add value to the system as well as for immediate treatment of a patient. Detecting the growth pattern will help to curb the spread of Brain Tumor.

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