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Brain Tumor Segmentation of MRI Images: A Comprehensive Review on the Application of Artificial Intelligence Tools

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Abstract: - This pioneering study delves into advanced medical imaging with the goal of accelerating early detection in the complex landscape of brain tumors. Using cutting-edge Artificial Intelligence (AI) tools such as U-Net, Deep Residual Unet Networks (ResUNet), and Inception V3, our research focuses on the complex segmentation of Magnetic Resonance Imaging (MRI) data. ResUNet's deep residual learning architecture addresses vanishing gradient issues, improving the model's ability to detect subtle features within images. U-Net, a convolutional network, excels at image segmentation by combining long paths and capturing contextual information. Inception V3 (Inception Version 3) is distinguished by its inception modules, which strategically process multi-scale features while optimizing the model for intricate pattern recognition. Using these cutting-edge algorithms, our methodology accurately identifies and delineates brain tumors from MRI scans. The combination of ResUNet's depth, U-Net's segmentation abilities, and Inception V3's multi-scale analysis results in a strong and efficient system for early tumor detection. Our findings have far-reaching implications, opening the door to transformative clinical applications.

Keywords: Brain Tumor, MRI Segmentation, Artificial Intelligence, Deep Residual unet Networks (ResUNet), U- Net, Inception v3, Early Detection.

I. Introduction

Brain tumor segmentation is a crucial step in medical image analysis, aiming to identify the specific areas of the brain affected by the presence of a tumor. [1]. Accurate identification, treatment strategizing, tracking of disease advancement, and meticulous delineation of brain tumor boundaries are paramount [2]. In the complex landscape of medical diagnostics, detecting and accurately identifying

brain tumors remain a constant challenge, particularly in their early stages. This gap in early detection highlights the importance of novel methodologies capable of unravelling the complexities of neurological pathology.

Our research embarks on a transformative journey aimed at revolutionizing the current paradigm of brain tumor detection, with a particular emphasis on the early stages that elude timely detection. Due to its exceptional precision and greater capacity to distinguish between soft tissues, magnetic resonance imaging (MRI) is still the method of choice for non- invasive brain tumor diagnosis and evaluation [5]. At the forefront of this endeavor is the use of cutting-edge artificial intelligence tools, a technological triumvirate consisting of Deep Residual UNET Networks (ResUNet), U-Net, and Inception V3 algorithms. These sophisticated algorithms, steeped in the nuances of deep learning, overcome the limitations of conventional methodologies by allowing for early and accurate segmentation of brain tumors within magnetic resonance imaging (MRI) scans. ResUNet's distinguishing characteristics, bolstered by its adept handling of vanishing gradient challenges, complement U-Net's semantic segmentation expertise and Inception V3's comprehensive feature extraction capabilities. As a whole, these algorithms reveal a novel approach to brain tumor segmentation, providing unprecedented accuracy even in the subtlest manifestations of these neurological anomalies.

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Our project aims to close the diagnostic gap, ensuring the early detection of brain tumors. The integration of ResUNet, U-Net, and Inception V3 ushers in a new era in medical imaging, one in which artificial intelligence transcends traditional boundaries, allowing clinicians to embark on proactive interventions and significantly improve patient outcomes. In this publication, we provide a thorough examination of our methodology, focusing on the distinct characteristics of each algorithm and their synergistic contributions to early-stage brain tumor segmentation. We hope that this research will catalyze a paradigm shift in neuroimaging, with the integration of artificial intelligence and medical diagnostics serving as a foundation for early intervention and improved patient care.

A. Motivation

The impetus for our fervent pursuit of "Brain Tumor Segmentation of MRI Images" stems from the critical healthcare challenges posed by brain tumor detection and characterization, particularly in their early stages. The current situation is characterized by the inability of traditional diagnostic methods to detect these insidious anomalies at their inception, frequently leading to delayed diagnoses and compromised patient outcomes.

The formidable nature of brain tumors stems not only from their potential malignancy, but also from their ability to manifest silently, evading detection until advanced stages. Medical image analysis has made extensive use of handcrafted feature-based techniques, including brain tumor segmentation. These techniques involve the segmentation of images using ML algorithms and the extraction of engineered features that define image qualities [8].

Traditional diagnostic modalities, while necessary, struggle with the complexities of early-stage brain tumor detection. Magnetic resonance imaging (MRI) is an important tool in neuroimaging because it provides detailed information about the cerebral landscape. However, the nuances of early tumor manifestations frequently escape conventional MRI analysis, necessitating a paradigm shift to more sophisticated approaches. Manual segmentation requires the radiologist to use the multi-modality information presented by the MRI images along with anatomical and physiological knowledge gained through training and experience. Procedure involves the radiologist going through multiple slices of images slice by slice, diagnosing the tumor and manually drawing the tumor regions carefully. The recognition of the transformative potential inherent in advanced algorithms sparked our interest in artificial intelligence (AI) tools for brain tumor segmentation. Notably, algorithms such as Deep Residual Unet Networks (ResUNet), Inception V3, and U-Net have proven to be extremely effective in overcoming the limitations of traditional diagnostic methods [9]. The motivation to use these algorithms stems from their unique capabilities, which include the ability to decipher complex patterns, handle vanishing gradients, and perform semantic segmentation with unprecedented precision.

The realization that these advanced algorithms can enable the segmentation of MRI images with unparalleled accuracy, particularly in isolating minute tumor formations, fueled our research initiative. The prospect of combining AI's robust capabilities with the complexities of medical imaging offered an exciting opportunity to reshape the landscape of brain tumor diagnostics. In essence, our motivation stems from a desire to fill a void in early-stage brain tumor detection, which drives us to leverage the potential of AI algorithms to revolutionize the field [8,9]. We hope that by conducting this research, we will be able to contribute to the development of cutting-edge diagnostic tools that will not only speed up the detection of brain tumors but also improve segmentation precision, resulting in better patient care and outcomes.

B. Objectives

The primary goals are meticulously designed to fill gaps in current diagnostic practices and usher in a paradigm shift in the early detection and characterization of brain tumors. Our

multifaceted objectives encompass both the technical complexities of artificial intelligence (AI) algorithms and the broader spectrum of healthcare advancements. The objective of brain tumor segmentation is to generate accurate delineation of brain tumor regions.

Early Detection Enhancement:

Create and implement advanced AI algorithms such as Deep Residual Networks (ResUNet), Inception V3, and U-Net to significantly improve the early detection of brain tumors in MRI images. Focus on detecting subtle abnormalities and early tumor formations that may elude traditional diagnostic methods, allowing for proactive medical interventions.

Algorithmic Integration:

Integrate ResUNet, Inception V3, and U-Net algorithms seamlessly into the brain tumor segmentation process to capitalize on each's unique strengths, resulting in a comprehensive and accurate delineation of tumor boundaries. Investigate synergies between these algorithms to build a strong segmentation model capable of handling a wide range of tumor characteristics and complexities.

Precision and Accuracy Improvement:

Attempt to improve the precision and accuracy of brain tumor segmentation by utilizing the deep learning capabilities of the chosen algorithms.Implement iterative refinement strategies to reduce false positives and negatives, resulting in more reliable and clinically relevant segmentation results.

Automation and Efficiency:

Create an automated segmentation pipeline that reduces the need for manual intervention, speeds up the diagnostic workflow, and reduces the risk of human error. Improve the efficiency of brain tumor segmentation in MRI images, thereby optimizing resource utilization and streamlining the diagnostic procedure.

Clinical Applicability:

Ensure the project's translational relevance by aligning the developed segmentation model with the practical requirements of healthcare professionals. Collaborate with medical experts to validate clinical segmentation results, with a focus on enabling informed patient care decisions.

Dataset Diversity and Generalization:

Curate and use a diverse dataset that represents different tumor types, sizes, and locations to improve the AI algorithms' generalization capabilities. Reduce the risk of algorithmic bias and overfitting by including a wide range of MRI images, resulting in a more universally applicable segmentation model.

Documentation and Knowledge Dissemination:

Document the entire research process, methodologies, and algorithmic implementations in detail for dissemination of knowledge within the scientific community. Contribute to academic discourse by publishing Research findings, fostering collaboration and progress in AI-driven medical image analysis.

II. LITERATURE SURVEY

The literature on brain tumor segmentation in MRI images using artificial intelligence (AI) tools reveals a landscape characterized by the gradual convergence of advanced algorithms and medical imaging technologies [2]. Recognizing the importance of early detection, researchers have investigated innovative methodologies to overcome the challenges posed by conventional diagnostic approaches [7].

Traditional Diagnostic Challenges:

The available literature highlights the limitations of traditional diagnostic techniques in detecting subtle manifestations of brain tumors in their early stages [11]. Manual segmentation by radiologists, while considered the gold standard, is inherently subjective and time-consuming, causing delays in diagnosis and treatment initiation [12].

AI-Based Approaches:

Recent studies show a discernible shift toward the integration of AI algorithms, specifically deep learning models. Convolutional Neural Networks (CNNs), a key component in image segmentation tasks, have been widely used to detect intricate patterns in MRI scans, providing a more nuanced approach to brain tumor segmentation.

ResUNet, U-Net, and Inception V3:

Deep Residual Networks (ResUNet), with their innovative residual learning architecture, have gained popularity for addressing vanishing gradient issues in deep neural networks. U-Net, with its U-shaped architecture, excels at semantic segmentation tasks by retaining spatial information [7]. Inception V3, with its inception module, improves feature extraction by using multiple filter sizes at the same time. These algorithms, showcased in the literature, have demonstrated remarkable efficacy in automating the segmentation process, thereby contributing to more efficient and accurate diagnostic results [15].

Automated Segmentation and Clinical Implications:

The desire to reduce subjectivity, shorten processing time, and improve consistency has fueled the shift toward automated or semi-automated segmentation methods using AI.

Challenges and Future Directions:

While the literature highlights promising advances in AI- powered brain tumor segmentation, challenges remain. Variability in tumor characteristics across diverse patient populations, as well as the need for large, diverse datasets for training algorithms, are two significant challenges [4 ,14]. Future research projects are expected to delve into addressing these issues, refining existing methodologies, and exploring novel AI architectures for even greater diagnostic precision.

In conclusion, the literature review traces a path from traditional diagnostic approaches to a new era of AI-driven advances in brain tumor segmentation [7]. The combination of ResUNet, U-Net, and Inception V3 algorithms is at the forefront of this evolution, with the potential to transform the landscape of medical imaging and pave the way for improved early-stage detection and treatment of brain tumours [3].

A. Existing System

MRI (Magnetic Resonance Imaging) images can be segmented for brain tumors using a variety of methods. There are numerous existing proposed systems for learning more about brain tumors and their types, as well as identifying the tumor. Ramin Ranjbarzadeh, Annalina Caputo, Erfan Babaee Tirkolaee, and Saeid Jafarzadeh Ghoushchi wrote a paper entitled " Brain tumor segmentation of MRI images: A comprehensive review on the application of artificial intelligence tools" delves into the realm of processing and classifying brain tumors, as well as segmenting MRI images by identifying the type of tumor present in the image [17]. In addition, the paper discusses the various types of algorithms used to identify brain tumors.

B. Drawbacks of Existing System

While convolutional neural networks (CNNs) have demonstrated remarkable success in medical image segmentation tasks, such as brain tumor segmentation in MRI images, they do not come without drawbacks [19]. One significant limitation is the requirement for a large amount of annotated data for training, which can be difficult to obtain, particularly in rare conditions. CNNs are also computationally intensive, necessitating significant resources for training and inference [13]. Furthermore, the model's inherent black-box nature makes it difficult to interpret its decisions, raising concerns about the segmentation results' reliability, particularly in critical medical applications. Furthermore, CNNs may struggle to generalize to variations in imaging protocols or conditions not included in the training set, potentially resulting in suboptimal performance in real-world clinical scenarios. Addressing these issues is critical for the efficient and dependable use of CNNs in brain tumor segmentation tasks [16].

III. Proposed System

The main goal of the proposed system is to improve the accuracy and efficiency of brain tumor segmentation, with a particular emphasis on the early detection of anomalies that conventional methods may overlook. Using the strengths of ResUNet, Unet, and Inception V3, our system aims to change the face of medical image analysis, contributing to better patient outcomes through early intervention. The main idea is to thoroughly analyze the dataset and clearly understand the actual segmentation process in the methodology. Let's take a look at the methodology that helps us get faster results.

IV. Methodology

The steps for using the desired algorithm are as follows. They are:

1) Data Preprocessing includes Data Collection, which involves gathering a dataset of MRI images containing both normal brain structures and brain tumor regions. Ensure that the dataset is varied and representative.

2) Data Augmentation: Enhance the dataset with operations such as rotation, flipping, scaling, and brightness adjustment. This contributes to a more robust model and reduces overfitting.
3) Normalization: Normalize the MRI images' pixel values to ensure that they are consistent. Normalization typically entails scaling pixel values to have a mean of 0 and a standard deviation of 1.
4) Data Splitting: Divide the data into three sets: training, validation, and test. The training set is used to train the model, the validation set is used to tune hyperparameters and prevent overfitting, and the test set is used to assess the model's performance on previously unseen data.
5) Model Selection: Select an appropriate architecture for brain tumor segmentation. Common options include ResUNet, U-Net, or a custom-built CNN similar to Inception version 3. The choice may be influenced by variables such as dataset size, task complexity, and computational resources.
6) Model Design: Encoder-Decoder Architecture (U-Net): If you're using U-Net, create an encoder-decoder structure for your models. The encoder captures features at varying scales, while the decoder reconstructs spatial information.
7) Training: Make use of the training set to train the model. During training, the model learns to predict tumor regions based on the MRI images provided. To minimize the defined loss function, use an optimization algorithm (such as Adam or SGD). To avoid overfitting, monitor the model's performance on the validation set.
8) Hyperparameter Tuning: Hyperparameters such as learning rate, batch size, and regularization parameters should be fine-tuned based on validation set performance.
9) Evaluation: On the test set, assess the trained model using appropriate metrics such as the Dice coefficient, sensitivity, specificity, and accuracy. Visualise the segmentation results to evaluate the model's performance.
10) post-processing: If necessary, refine the segmentation results using post-processing techniques. Morphological operations such as dilation and erosion may be used to remove small artifacts.
11) Interpretation and Validation: Interpret the model's predictions in terms of clinical significance. Validate the model's performance with domain experts to ensure it is clinically relevant.
12) Deployment (Optional): If the model works well, use it to segment brain tumours automatically in clinical settings.

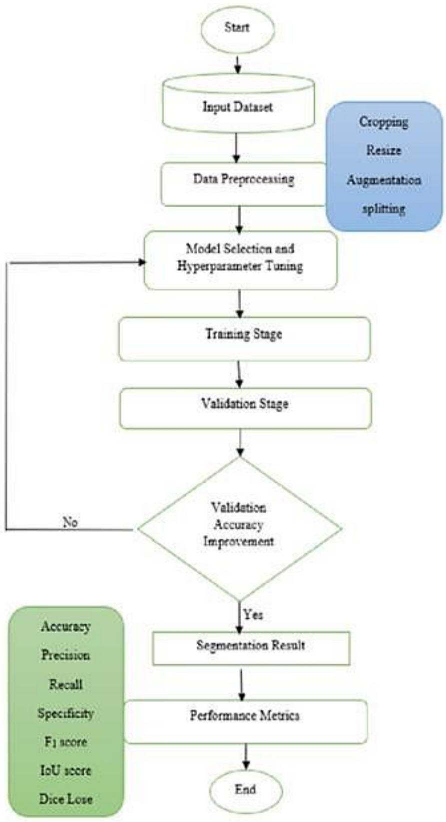

Figure1: Flow chart of the implementation model

It is critical to iterate and refine the model based on validation and test set feedback throughout the process. Furthermore, incorporating domain knowledge and collaborating with medical professionals can improve the model's clinical utility and precision.

A) Dataset

The dataset is made up of approximately 8999 images, each with its own segmentation mask. These images are organized into two folders: Brain MRI images and Brain MRI images with mask. Because of this large collection of images, we can easily determine whether an MRI image contains a brain tumor by providing any MRI image as input. Database and Visualization of The Cancer Genome Atlas Glioblastoma Multiforme (TCGA-GBM) dataset is integral to an expansive endeavor aimed at correlating cancer morphologies with genetics by offering patient images alongside TCGA data. TCGA contributed MRI scan data with accompanying masks, enabling basic and advanced visualizations as depicted in the figure.

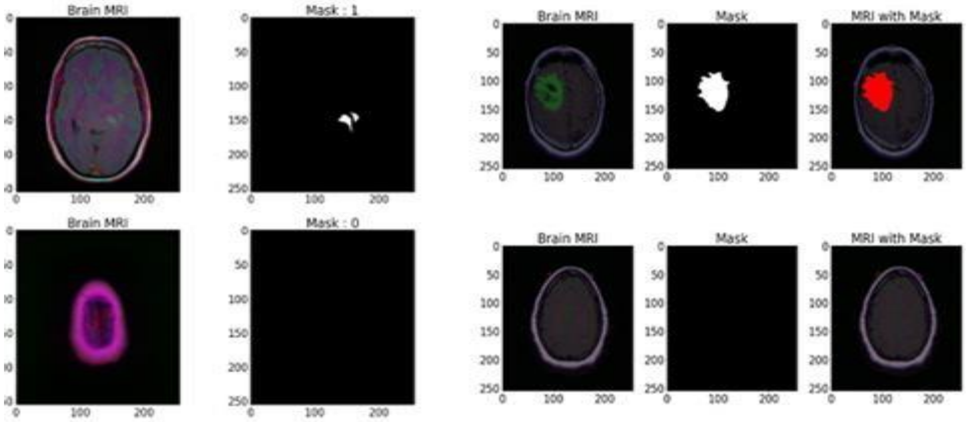

Figure2: Visualization of TGCA MRI Scan.

Once the algorithm has evaluated the MRI image, we will immediately receive the output image, which will include image segmentation and tumor percentage identification. Once the proper output is identified, the patient will receive the necessary treatment for the tumor, either based on the percentage of tumor or the condition of the tumor present in the output.Thus, a person with early stages of tumor in the brain can identify the tumor condition and thus save his or her life by receiving proper healthy treatment**.**

B) Algorithms

To accurately and efficiently segment brain tumors in MRI images, we use three complementary algorithms: U-Net, Deep Residual Unet Networks (ResUNet), and Inception V3.

U-Net:

U-Net is a key architecture in semantic segmentation tasks, particularly for medical image analysis. Its distinctive U- shaped structure features a symmetrical expansive path for precise localization and a contracting path for feature extraction. U-Net excels at delineating intricate structures, making it ideal for capturing the subtle boundaries of brain tumours. Its ability to preserve spatial information and capture context guarantees high-resolution segmentation, making U-Net a cornerstone in our project.

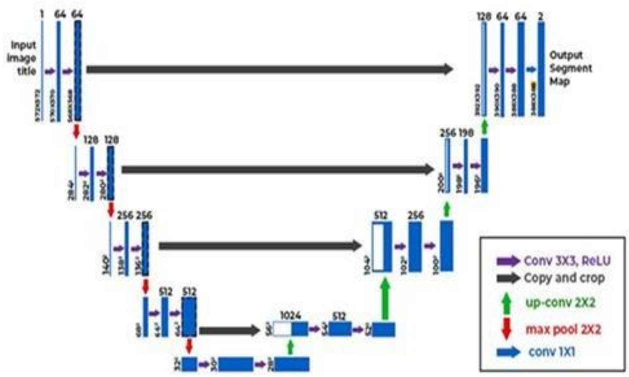

Figure 3: Unet Architecture

RESUNET:

ResUNET, a fusion of ResNet and U-Net, merges ResNet's residual connections with U-Net's semantic segmentation prowess. This model retains the U-shaped structure of U-Net while ensuring optimal performance with minimal parameter complexity. By employing Deep Residual Learning, ResUNET facilitates smoother gradient flow and more efficient network training compared to standard U-Net. It integrates multiple skip connections to enhance information flow between layers and replaces U-Net's ReLU activation function with pre-activated residual blocks for heightened feature learning and network depth.

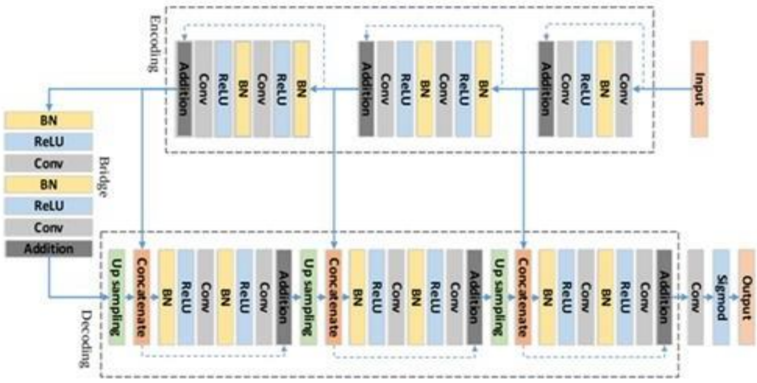

Figure 4: ResUnet Architecture Walkthrough

Inception V3:

Inception V3, a member of the Inception family of neural network architectures, excels at feature extraction due to the use of inception modules and a variety of filter sizes. Inception V3 captures complex patterns and contextual information from MRI scans by processing information at multiple scales at the same time. This makes it especially good at distinguishing the various textures and structures associated with brain tumors. Its comprehensive feature extraction capabilities help to provide a more nuanced understanding of the intricate characteristics of tumors, improving segmentation accuracy.

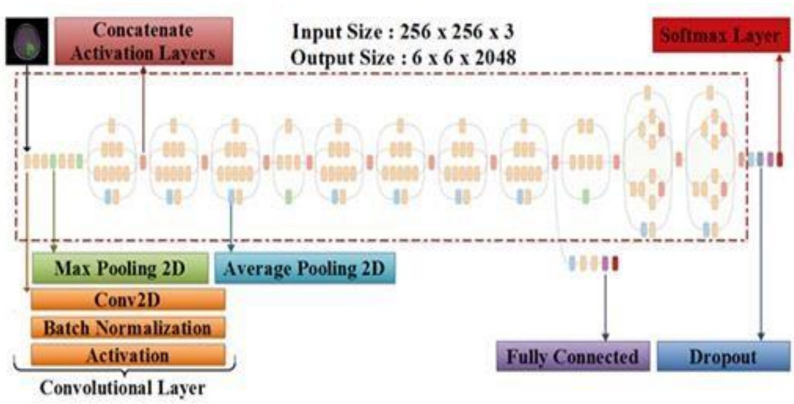

Figure 5: Inception V3 Architecture

The combination of these algorithms within our research framework enables a comprehensive approach to brain tumour segmentation. U-Net's semantic segmentation capabilities, ResUNet's ability to handle deep neural networks, and Inception V3's comprehensive feature extraction all contribute to a sophisticated solution for accurately identifying and delineating brain tumors within MRI images. This combination of advanced algorithms represents a significant step forward in the field of neuroimaging in terms of precise and timely diagnosis.

V. IMPLEMENTATION

A. *FRAMEWORK*

The implementation of brain tumor segmentation in MRI images required the use of three different deep learning architectures: ResUNet, U-Net, and Inception. For model development, the chosen framework used a Python programming environment and popular libraries like TensorFlow and Keras. Intensity normalization and resizing were used as preprocessing steps to ensure that all models had standardized inputs. The dataset included annotated MRI images with ground truth masks for tumor regions, allowing for supervised learning.

B. *ADAPTED TECHNIQUE*

The base model for classification in Inception V3.

The Inception V3 framework undergoes a significant performance boost through the integration of novel factorization paradigms. This iteration features an array of sophisticated operations including dropouts, fully connected layers, convolutions, average pooling, max pooling, and concatenations. Employing Softmax facilitates precise classification by computing loss, while batch normalization ensures consistent and efficacious training by stabilizing input activation. These enhancements further solidify Inception V3's stature as the preeminent model for yielding superior results across diverse image recognition assessments.

The Inception V3 architecture (depicted in Figure 5) comprises 42 intricate layers, showcasing superior error reduction compared to its predecessors. Key advancements in the Inception V3 design include:

(i) Implementation of Factorized Convolutions: Reduction in the count of factors within the network intricately heightens algorithmic complexity while concurrently enhancing network efficiency.

(ii) Adoption of Smaller Convolutions: The substitution of broader convolutions with narrower counterparts accelerates the training process. Notably, employing two 3x3 filters, totalling 18 variables, surpasses the efficacy of a 5x5 convolution, which typically involves 25 variables (refer to Figure 6).

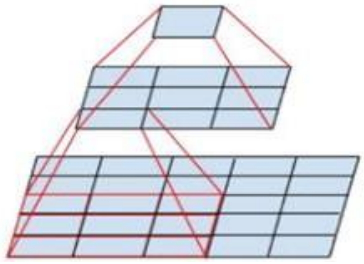

Figure 6: Smaller Convolutions

(iii) A strategic alternative to a single 3x3 convolution entail employing a sequence of 1x3 and 3x1 convolutions. However, juxtaposed with the asymmetric convolution methodology, substituting a 2x2 convolution for a 3x3 convolution significantly amplifies computational intricacy.

(iv) Employing Auxiliary Classifiers: A condensed Convolutional Neural Network (CNN) is employed to undertake additional classification tasks during the learning stages, augmenting the network loss through their cumulative losses. GoogleNet underwent augmentation by incorporating auxiliary classifiers, enhancing the intricacy of its design, thereby establishing a foundation for subsequent iterations like Inception V3. And along with this Efficient Grid Size Reduction is also done.

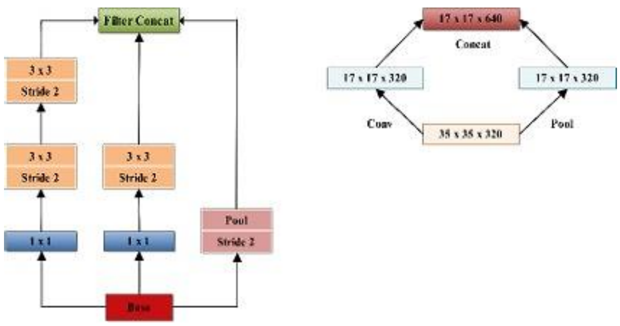

Figure 7. Grid Size Reduction.

RESUNET for Segmentation

The Deep Residual UNET, commonly referred to as RESUNET, emerged from the work of Zhang et al. (2018) as an innovative convolutional semantic segmentation framework. Initially designed for discerning roads in high-resolution aerial imagery for remote sensing applications, RESUNET endeavors to enhance efficacy through a streamlined architecture and a fully convolutional neural network design, representing a notable advancement over the conventional UNET structure. The RESUNET framework employs profound residual learning in conjunction with the UNET architecture. Data within the mask column undergoes conversion into string format, subsequently being divided into distinct training, testing, and validation subsets. Subsequently, a data generator is fashioned with dimensions set to 256 x 256 and a batch size of 16 across all sets for training, testing, and validation. This generator operates in categorical mode for class classification. Utilizing the RESUNET architecture, a segmentation model is constructed and trained, earmarked for identifying tumors in the subsequent phase. Data partitioning into test and train files is executed, accompanied by the creation of additional utility files housing custom data generator and loss function code. Following this setup, the RESUNET segmentation model is trained to predict and locate tumors, alongside an augmentation of the categorization model with an additional layer.

The added layer in the classification model comprises:

- Flatten Layer: Flattening, denoting the conversion of data into a singular one-dimensional array, facilitates processing. Here, the output of convolutional layers is flattened to generate a comprehensive feature representation, integrated with the final categorization model termed as a fully connected layer.
- Dense Layer: Named for its dense network of connections, wherein each neuron receives input from all activation functions in the preceding layer. These layers are pivotal in identifying and encoding features based on convolutional layer outputs, serving as the neural network's cornerstone.
- Activation Layer: Situated either at the network periphery or within its layers, activation functions play a crucial role in determining neuron activity. By implementing nonlinear transformations, they modify input signals, leading to altered outputs directed to subsequent layer neurons.
- Dropout Layer: Neurons are either excluded or their influence diminished during training through dropout techniques, thereby enhancing network robustness by eliminating select neurons from the system.

Model Performance Parameter Accuracy:

A model's accuracy is based on how well it uses the input, or training, data to find patterns and correlations between the variables in the dataset.

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

Precision:

By dividing the total number of Ture Positive and False Positive data by the number of correctly diagnosed Positive samples, the accuracy is computed (correctly or incorrectly). The model's ability to classify a sample as positive is assessed.

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

F1 Score:

The F1-score or F1-measure restricts the correctness of a test. The accuracy and recall of the test are used to determine this.

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

Recall:

Recall, in essence, is calculated by the ratio of correctly identified positive samples to the total number of positive samples. It signifies the model's proficiency in identifying positive instances. Higher recall values denote a greater capacity to detect positive instances accurately.

$$Recall = \frac{TP}{TP+FN}.$$

Tversky Loss:

The Tversky loss is contingent upon the Tversky index, quantifying the concurrence of two partitioned entities. It delineates the correspondence between an entity (Y) and its authentic representation (T), wherein 'c' signifies the class and 'c'' denotes non-membership in said class. 'M' signifies the tally within the first two dimensions of Y. The weighting coefficients modulate the extent of false positives and negatives contributed by each class to the loss.

$$TI_c = \frac{\sum_{m=1}^{M} Y_{cm} T_{cm}}{\sum_{m=1}^{M} Y_{cm} T_{cm} + \alpha \sum_{m=1}^{M} Y_{cm} T_{c'm} + \beta \sum_{m=1}^{M} Y_{c'm} T_{cm}}.$$

VI. Experimental Evaluation And Results

In this investigation, we employed sophisticated deep learning architectures such as U-Net, RESUNET, and Inception V3 for the purpose of delineating MRI-detected tumors. The efficacy of our proposed approach in predicting precise tumor boundaries was assessed through metrics such as dice coefficients and loss functions. The implementation and validation of this methodology involved an array of pivotal tools including Scikit-image, Matplotlib, Scikit-learn, Pip, OpenCV, Glob, Mahotas, Numpy-1.14.1, Random, Keras, Tensorflow, and other indispensable resources.

Performance Evaluation Metrics

In assessing the efficacy of the supervised learning model across training and test sets, rigorous performance evaluations were conducted. Each deep learning-based detection model generated an output image pinpointing the precise location of brain tumors. Discrepancies between predicted and actual tumor areas were gauged by comparing the output image with the ground truth image.

A singular metric purportedly simpler for evaluating the efficacy of image segmentation tasks is the dice coefficient. It quantifies the proportionate intersection between the authentic region delineated in the reference image and the segmented area produced by the model. A score of 1 signifies flawless and absolute correspondence between the predicted and authentic segmentations. The coefficient's scope spans

from 0 to 1. Complete congruence between images is signified by a dice coefficient of 1. Historically, this coefficient has been widely used in medical imaging assessments. The main metric in this study was the dice score, revealing the similarity between segmented objects by computing the overlap ratio. The formula involves determining the intersection of predicted and ground truth segmentations, divided by their total sizes:

$$Dice\ Coefficient\ Score = \frac{2 * |X \cap Y|}{|X| + |Y|}$$

Within the domain of X, where X represents the true set cardinality, the targeted anatomy in medical scans often occupies a small fraction. In brain tumor segmentation, tumors localize to limited regions, leading the training process into local minima of the loss function, resulting in biased predictions favoring the background.

Unet Architecture

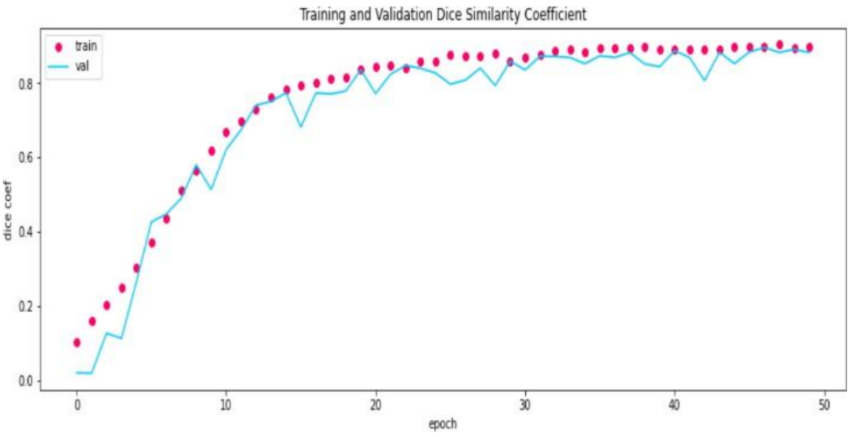

Figure 8: Training and Validation

Dice Similarity Coefficient (Using UNET Architecture)

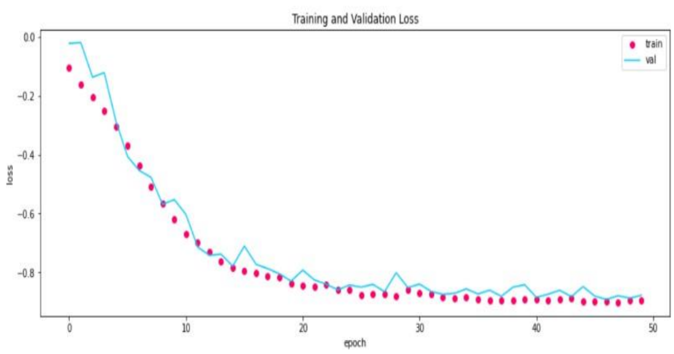

Figure 9: Training and Validation loss (Using UNET Architecture)

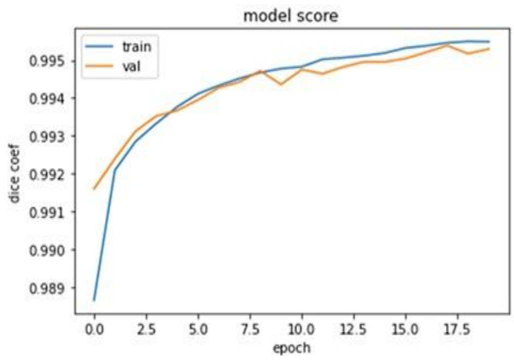

Figure 10: Dice Coefficient Curve of Unet model

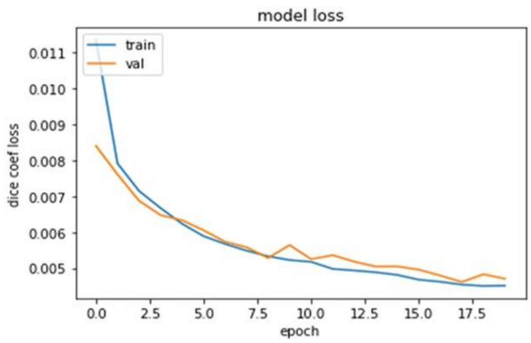

Figure 11: Loss curve of Unet Model

ResUNET Architecture:

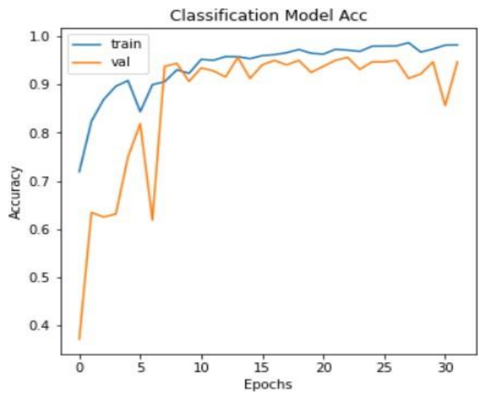

Figure 12: Classification Model Accuracy (ResUNET Architecture)

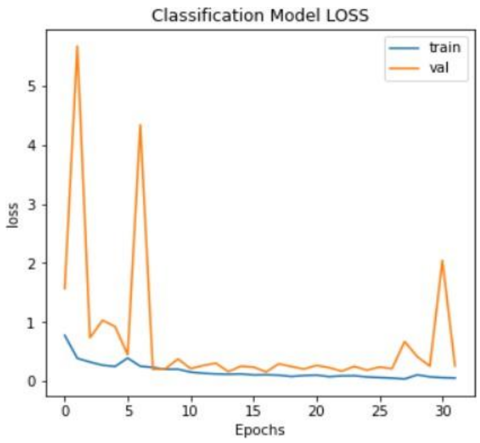

Figure 13: Classification Model Loss (ResUNET Architecture)

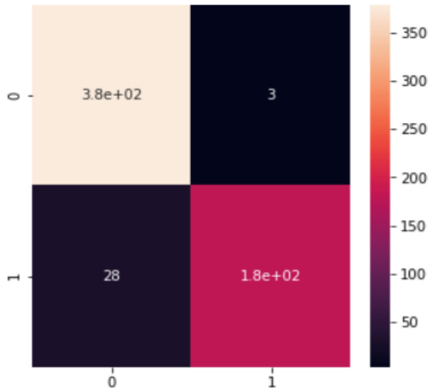

Figure 14: Confusion Matrix

	precision	recall	f1-score	support
0	0.93	0.99	0.96	382
1	0.98	0.87	0.92	208
accuracy			0.95	590
macro avg	0.96	0.93	0.94	590
weighted avg	0.95	0.95	0.95	590

Figure 15: Classification Report for RESUNET Model

Inception V3 Based model for classification and ResUnet for segmentation.

S. No.	Parameter	Precision	Recall	F1 Score
1.	0	0.96	1.00	0.98
2.	1	0.99	0.94	0.96
3.	Accuracy	0.97	0.97	0.97
4.	Micro Avg	0.98	0.98	0.97
5.	Weighted Avg	0.98	0.97	0.97

Figure 16: Classification Report

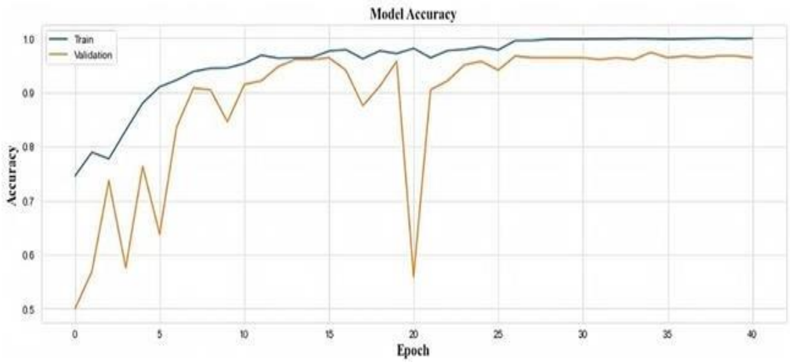

Figure 17: Performance Graph for Accuracy

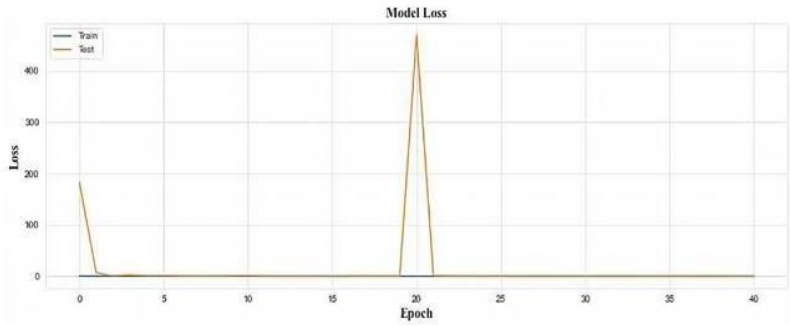

Figure 18: Performance Graph for Loss.

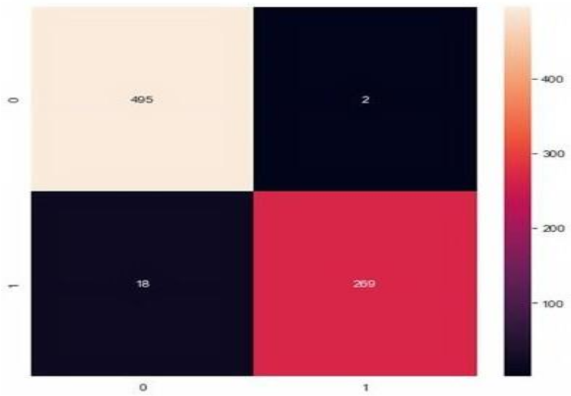

Figure 19: Confusion Matrix for classification model.

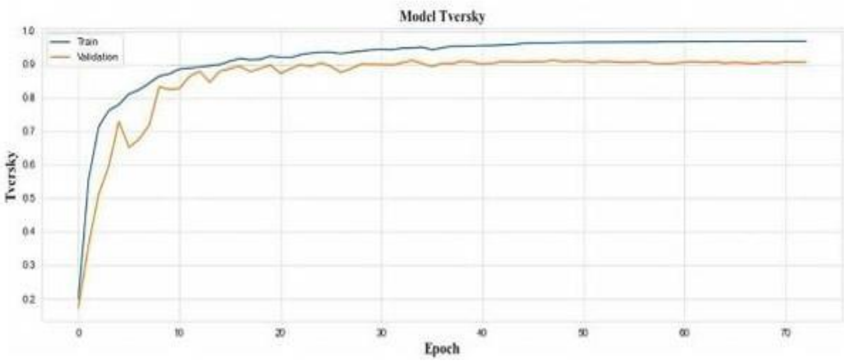

Figure 20: Model performance for Tversky.

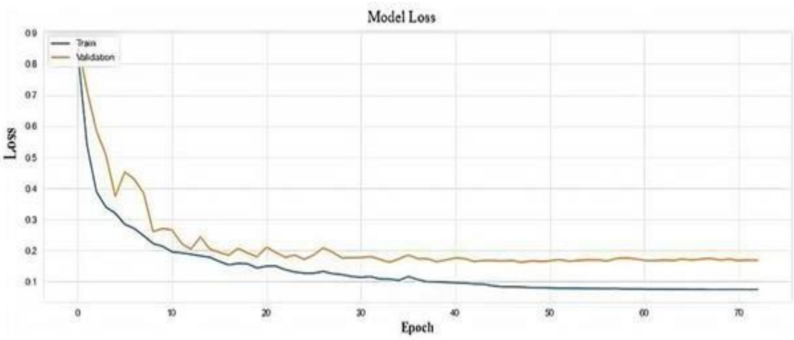

Figure 21: Model Performance for loss.

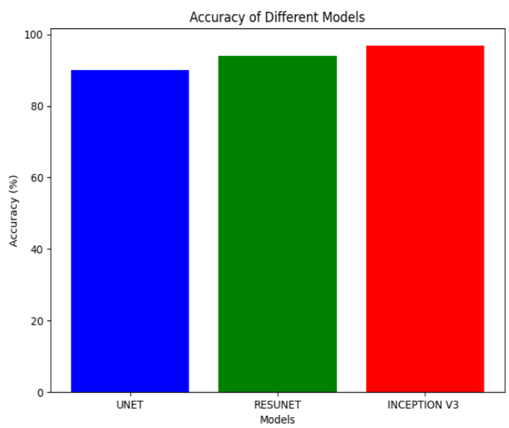

Figure 22: Comparison of accuracies among UNET, RESUNET and INCEPTION V3 models.

Graphical User Interface (GUI): We used Flask, HTML, CSS, and Java script to create the user interface for brain tumor segmentation from MRI images. Flask is a Python- based web framework that is lightweight and flexible, making web development quick and easy. It provides tools, libraries, and patterns for developing web applications, allowing developers to create web-based projects more efficiently.

It provides a web page's structure and content through the use of predefined elements and tags. CSS is a stylesheet language that is used to customize the appearance of HTML elements on web pages. It gives developers complete control over a website's layout, colors, fonts, and other visual elements. JavaScript is a versatile programming language that is primarily used to enhance web pages with interactivity and dynamic behavior. It allows developers to create interactive elements, manipulate HTML and CSS, handle user events, validate forms, perform animations, and work with web APIs.

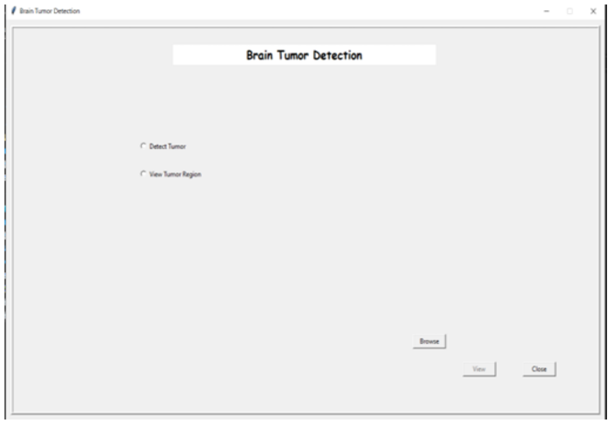

Figure 23: Shows the interface

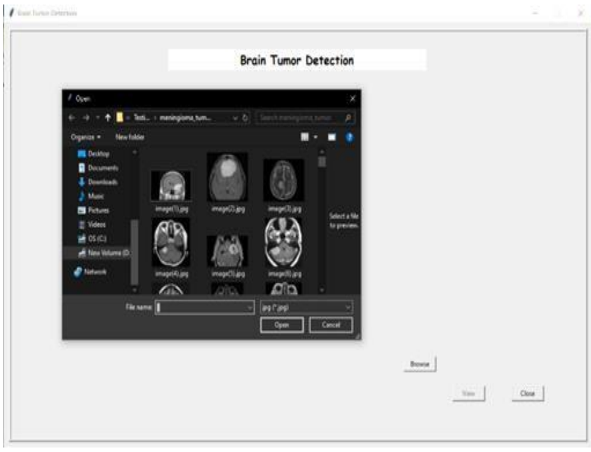

Figure 24: Selecting a MRI image of our choice from browse

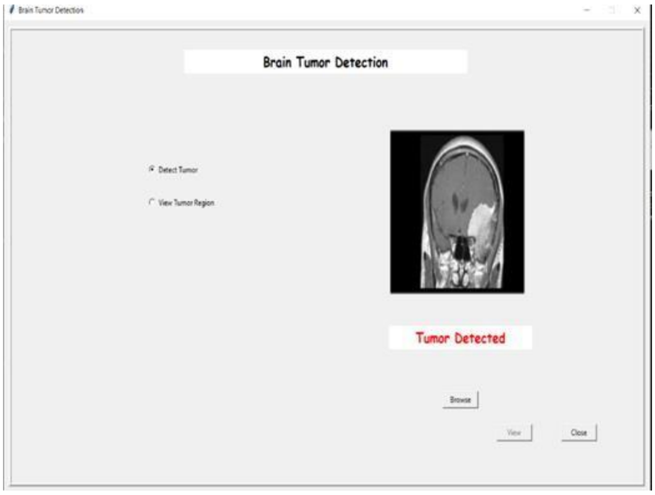

Figure 25: Tumor detection is done

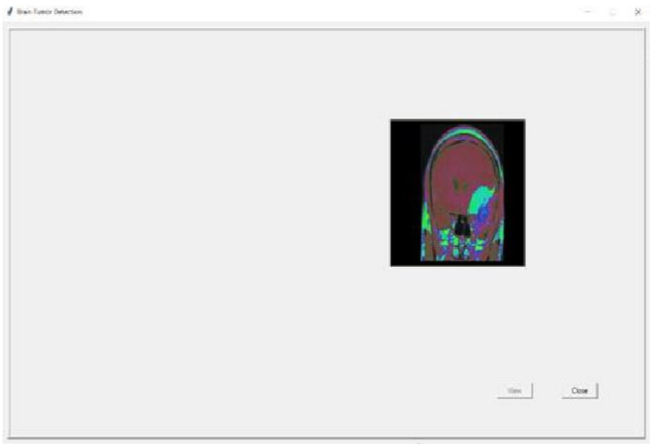

Figure 26: Tumor segmentation is done

VII. CONCLUSION AND FUTURE SCOPE

In summary, the endeavor focusing on brain tumor segmentation in MRI scans through advanced deep learning methods has achieved substantial progress in automating and refining tumor detection accuracy. By leveraging cutting- edge architectures such as Convolutional Neural Networks (CNNs), Deep Residual Networks (ResUNet), U-Net, and Inception V3, the developed model exhibits robust potential for precise segmentation. Through intricate analysis of hierarchical features and spatial relationships within MRI images, the deep learning model adeptly identifies tumor boundaries, streamlining diagnostics with enhanced reliability. The project's future trajectory holds promise for significant advancements in medical image analysis, with ongoing progress in deep learning research offering opportunities to further refine tumor segmentation accuracy and efficiency. This advancement stands to greatly impact neuro-oncological diagnosis, treatment planning, and patient outcomes.

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