© December 2024 | IJIRT | Volume 11 Issue 7 | ISSN: 2349-6002

Brain Tumor Classificaton and Segmentation Using Deep Learning

Sourav Mandot Alais Jain[1], Harsh Jadhav[2], Pranjal Pandit[3]
[1,2,3] *Department of Computer Science & Engineering (Artificial Intelligence), BRACT'S , Vishwakarma Institute of Information Technology, Pune, Maharashtra, India.*

Abstract: **Among all types of cancers, brain cancer has been among the most common affecting many people. The disease is now endangering lives. Early detection is crucial for making life-saving interventions. MRI is a very powerful device for detecting different brain abnormalities and widely used by radiologists and physicians. We propose Deep learning-based convolutional neural network techniques to identify different types of brain cancers. The proposed model uses large datasets with five classes (meningiomas, gliomas, pituitary, Neurocitoma, Schwannoma tumors). The model is developed based on Residual Network or ResNet-50 and has a special designed architecture to learn abnormal complex data features. This helps doctors decide whether the patient has the disease. With deep learning technology, it offers a more accurate, effective, faster way to identify brain tumors. The proposed method achieves accuracy of 99.08%. Experimental results show the efficiency of the proposed method for BT multi-class categorization.**
A brain tumor is when there is an abnormal growth of cells somewhere in the brain or in its central nervous system. It can be primary or it can metastasize. A Magnetic Resonance Imaging scan (MRI) is one of the most common means of detection of brain tumors. However, the modern-day best-in-class format for brain tumor segmentation such as the U-Net architecture would still be preferred because radiologists may differ in perspective. In America only, over 160.000 people live with brain and other nervous system cancers, and thus timely detection of these tumors becomes vital. In this said paper, three models; Regular U-Net, Upgraded U-net, and Attention U-net are shown to segmentation against the brain tumor and compared using Dice Score Coefficient (DSC). Among these three models, regular U-Net renders the best DSC of 0.3902, 0.6877, and 0.6534 for the Necrotic, Edema, and Enhancing Tumor mask, respectively. These include promising findings as well as floors for future improvements. Research might investigate new methods of pre-processing data or alternate designs of model architecture to bring about an improvement in segmentation accuracy. Such findings illustrate the potential of advanced deep learning models like UNet in brain tumor detection, along with adding and comparing various models and techniques to further enhance each model's performance for more coherent and accurate results critical in timely and right patient care.

Keywords- **MRI, U-net, ResNet50,**

1. INTRODUCTION

1.1 Background

Abnormal growths of tumorous tissues in the brain are termed brain tumors. These tumors have classifications of either benign or malignant. They should be primarily diagnosed by means of medical imaging techniques, where MRI (Magnetic Resonance Imaging) scan is considered a well-known tool for tumor detection. An MRI scan is a special imaging technique where high-resolution images of the brain are furnished, with which the size, type, location, and indeed presence of a tumor may be assessed by a radiologist. However, such interpretation of scans is a subjective task and requires a good level of expertise. Small tumors or characteristics thereof can be missed by the most experienced radiologists, delaying diagnosis and treatment.

There are techniques like machine learning or more particularly deep learning techniques that used to automate brain tumor classification and segmentation. This has reduced human intervention and lack in diagnosis speed. Convolutional neural networks (CNNs) among the deep learning models have proved their effectiveness in image analysis tasks especially those related to medical imaging.

ResNet, which is short for Residual Networks, uses a series of residual blocks that enable the model to learn deeper representations without being affected by the problem of vanishing gradient, which is an ethical concern for deep networks. This feature ensures that ResNet50 is used in many complex image classification problems, such as tumor detection..

While CNNs have shown promising results, a major limitation is that they lack interpretability. These techniques can make deep learning models more understandable and sensible in a medical scenario.
This paper makes a study of brain tumor classification and segmentation using ResNet50 and U-net and also performing real time classification and comparing different deep learning models.

1.2 Problem Statement

Diagnosis of brain tumors through MRI scans involves complex tasks like tumoral classification and segmentation. Current methods are time-consuming and prone to human error. Tumor shapes, sizes, and textures can vary among patients, so tumor segmentation manually is often inaccurate. Even advanced machine learning techniques such as those based on Convolutional Neural Networks are often less interpretable, making it hard for medical practitioners to reason and understand the model's framework.
Therefore, this paper addresses these problems:
Improve the accuracy of brain tumor classification approaches with deep learning models, particularly ResNet50.
Automate the process of segmenting images of MRI brain scans to help radiologists quickly and accurately identify the borders of tumors.

1.3 Motivation

Classification of brain tumor and segmentation is essential for diagnosis and planning of treatment. Most traditional methods advocate manual workflow, which takes a lot of time and is often prone to several human errors. Improved functionality and performance, especially recently brought by the introduction of ResNet50 deep learning models, significantly increased the success rates of these operations. The more fundamental problem remains the opacity of deep learning models that inhibits their less use in clinical applications.

This study seeks to synergize the benefit of explainable AI into such a workflow by putting together the efficacy of deep learning with its transparency so that clinicians can trust the decisions made by AI models in their practice. Healthcare is a field where the decisions made by most AI systems really matter for patients. A motivation that brings this research study is to have an automated, accurate, and explainable tool that radiologists can use to detect brain tumors so that patient care can be enhanced.

1.4 Objective

"Targeting the goal of classifying and segmenting brain tumors via a deep learning-oriented classification and segmentation model using ResNet50, one such technique is expected to complement the model with Explainable AI techniques. Specifically, it attempts to, among others:

High-accuracy classification of brain tumors into glioma, meningioma pituitary tumors and normal brain tissue.
Accurately segment the tumor from MRI, where the tumor region will be differed from normal brain tissue.

2. RELATED WORK

2.1 Brain Tumor Classification

The research on classification of brain tumors has continued to be active in terms of MRI images. At first, it relied on the traditional machine learning approaches in which some texture, shape as well as intensity properties were manually extracted from MRI scans and processed into algorithms as Feature Extraction and Classification in Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN). Although quite promising, this approach would become limited when the application was made on diverse datasets, given that it would handcraft features.

In recent decades, deep learning techniques have changed the field, especially using deep architectures such as Convolutional Neural Networks (CNNs), by automatically learning from raw data, thus doing away with the human-engineered features. Multiple studies have demonstrated the efficacy of CNNs in classifying tumor types obtained from brain scans. For instance, (Review of li et al.., 2017) applied CNNs to classifying gliomas and meningiomas with over 90% accuracy. Most recently, ResNet50, with its very deep architecture and the benefit of residual connections, has been used to achieve very improved performance compared to other architectures on multiple classification tasks related to medical images.

2.2 Brain Tumor Segmentation

Tumor segmentation signifies the activity of outlining the tumor site from other surrounding tissues seen in medical images. Traditionally, the segmentation included thresholding, region growing, and active contours. However, for many applications, it could not solve the problem of the complexity and variability of tumor shapes.

During these days of deep learning, U-Net is considered a gold standard in segmentation pertaining to medical images. Primarily because of its encoder-decoder structure, it is an ideal architecture for pixel-level segmentation tasks. Recently, some ResNet-based architectures have been incorporated into U-Net to better extract features in the encoder part of the network.

For instance, (Review of yu et al, 2018)a ResNet-based U-Net model for brain tumor segmentation on LGG Segmentaion dataset, taken from kaggle, producing state-of-the-art results. The resultant model of ResNet50 along with U-Net showed highly efficient in segmenting complex tumor structure scanned using MRI.

3. LITERATURE REVIEW

The below table 1. Shows the research we have done on brain tumor Classification and segmentation

Paper Name	Publication	Model /Algorithm Used	Limitation/Future Scope
[18] Multimodal Brain Tumor Classification Using Deep Learning and Robust Feature Selection: A Machine Learning Application for Radiologists	Diagnostics	VGG16 and VGG19 extreme learning machine domain adaptation transfer learning	More no of features caused degradation in accuracy
[19]Advanced Deep Learning Approaches for Accurate Brain Tumor Classification in Medical Imaging	Symmetry	VGG-16, VGG-19, and Inception-V3 architectures with AQO optimize	crowdsourcing data collection and analysis
[20] A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network	Healthcare	Hybrid of CNNs and genetic algorithm HVS processing	FCN architecture for the classification
[21] Detecting brain tumors using deep learning convolutional neural network with transfer learning approach	International journal of imaging systems and technology	GoogleNet ResNet101 Transfer learning	Not given
[22] Development and Validation of a Deep Learning Model for Brain Tumor Diagnosis and Classification Using Magnetic Resonance Imaging	*JAMA Network Open*		he inclusion of different MRI views and addition of clinical information in predictive modeling may be associated with improved performance of the system
K-Net-Deep joint segmentation with Taylor driving training optimization based deep learning for brain tumor classification using MRI	*Imaging Science Journal*	K-Net-Deep joint segmentation Driving Training Taylor (DTT) algorithm Shepard Convolutional Neural Network (ShCNN)	Not given
Multi-Classification of Brain Tumor Images Using Deep Neural Network	IEEE	AlexNet ANN SVM KNN	Needs big dataset include different ages and races

[3] Automated brain tumor segmentation techniques— A review		This paper reviews automated brain tumor segmentation techniques using MRI, PET, CT, and multimodal imaging.	- Diversity of tumor shape, location, and size makes segmentation challenging - Limitations of individual imaging modalities (PET, CT, MRI) can affect segmentation accuracy - Multimodal techniques can address some limitations but also have their own limitation
[7] State of the art survey on MRI brain tumor segmentation.		1. Semiautomatic brain tumor segmentation methods 2. Fully automatic brain tumor segmentation methods 3. MRI-based brain tumor segmentation	- The current methods for brain tumor segmentation are not fully automatic and require further development to achieve higher accuracy and efficiency. - The accuracy and efficiency of the developed systems may not be at the desired level, and there is a need to explore and compare different classification techniques to improve the accuracy.
[8] Review of Brain Tumor Segmentation and Classification		- Segmentation algorithms: fuzzy c-means, k-means, convolutional neural networks, Particle Swarm Optimization (PSO) - Classification algorithms: support vector machines (SVM), K-nearest neighbors (K-NN), Nearest Subspace Classifier (NSC), Sparse Representation-based Classification (SRC), k-means	- Difficulty in segmenting brain tumors due to high variability in shapes and sizes - Room for improvement in segmentation accuracy, especially in the core and enhancing tumor regions - The method may not generalize well to other types of medical image segmentation tasks beyond brain tumor segmentation
[16] A deep learning architecture for brain tumor segmentation in MRI images		1. A novel fully convolutional network (FCN) architecture for brain tumor segmentation in MRI images. 2. The use of the Brain Tumor Segmentation (BraTS) challenge dataset provided by the MICCAI society.	- The reviewed methods may have limitations in terms of their effectiveness for brain tumor segmentation from MRI images - There is still room for improvement and further exploration in this research area
[17] A review on brain tumor segmentation of MRI images.		1. Conditional Random Field (CRF) 2. Fully Convolutional Neural Network (FCNN) 3. DeepMedic 4. Ensemble methods	- Accurately detecting and segmenting brain tumors from MRI data can be challenging due to the complex characteristics of tumors - The proposed method is semi-automatic, which could be seen as a limitation

			compared to a fully automated approach - There is still room for improvement in the overall performance of the brain tumor segmentation and classification, even though the proposed method shows improved results compared to the k-NN classifier
[15] Automated Segmentation and Detection of Brain Tumor from MRI		1. Convolutional Neural Networks (CNNs) for semi-automatic brain tumor segmentation 2. Knowledge-guided (KG) technique for automated brain tumor segmentation 3. k-Nearest Neighbors (k-NN) classifier with learned optimal distance metrics for pixel-level tumor/background classification	- The need to improve the robustness and accuracy of the segmentation algorithms - The need to further explore and evaluate advanced segmentation methods like region growing, genetic methods, fuzzy clustering, deformation, atlas methods, and artificial neural networks - The need to further explore and evaluate hybrid methods that combine different techniques like genetic algorithms, artificial neural networks, and support vector machines
[23] Self – activated segmentation practices of brain tumefaction in MR scan images: a study		- Conventional segmentation techniques: thresholding, edge-based, morphology-based, watershed, k-means, and Markov random field methods - Advanced segmentation techniques: region growing, genetic algorithms, fuzzy clustering, deformation-based, atlas-based, and artificial neural networks - Hybrid methods combining genetic algorithms, artificial neural networks, and support vector machines (SVM)	

4. METHODOLOGY

4.1 Dataset and Preprocessing

The study further uses the two broad datasets as follows:

LGG Segmentaion Dataset: This used widely for segmentation tasks and comprises MRIs from multiple modalities (FLAIR, T1, T1CE, and T2), together with ground truth segmentation masks. The images were appended to a 128×128×128 dimension for uniformity and computational economy.

Brain Tumor MRI Dataset: This dataset comprises labeled images indicating whether or not brain tumor abnormalities exist in the specimen and is designed for classification purposes.

Preprocessing Stages

Normalization: All intensities of pixels in MRI images normalized on the same range of [0, 1], ensuring consistency of input values into the neural network.

Augmentation: Addressing class imbalance and model generalization: Classification data: random rotations, flips, zooms, and shear transformations. Random flipping across spatial axes, rotation within a range of −10degree to 10degree , and zoom within a scalene range of 0.9 to 1.1are used in the augmentation of segmentation data.

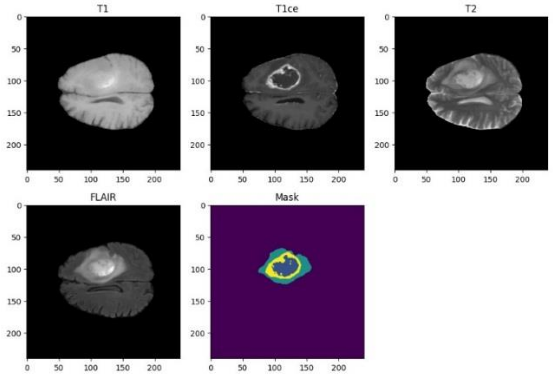

Figure 1Modalities

4.2 Model Architecture

Classification Module

The classification of tumor is done using the backbone of pre-trained ResNet50V2 model fine-tuned for four-class classification. The architecture comprises:

A global average pooling layer for feature extraction.

Fully connected layers along with a softmax activation final output layer for a multi-class probability distribution.

Segmentation Module

Segmentation task is achieved through a 3D U-net custom architecture enhanced:

Residual Blocks Promote deeper learning by gradients moving efficiently.

Attention Mechanism Attention layers were designed to focus saliently on tumor regions to suppress irrelevant backgrounds.

Output Layer: The output layer is converted into binary segmentation using sigmoid function activation to produce pixel-wise tumor masks.

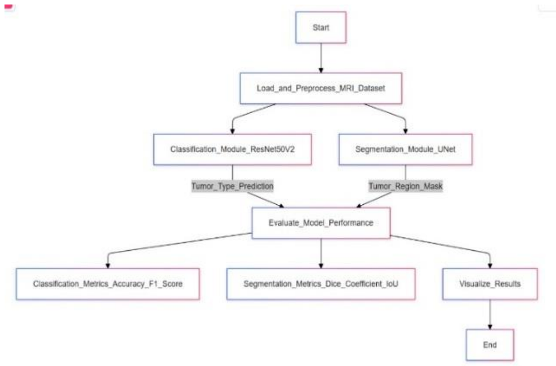

Figure 2Model Architecture

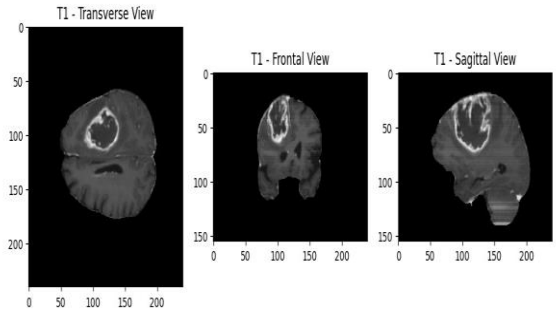

Figure 3Presentation of these 3 Planes

4.3Training and Validation

Data Generators

Separate data generators were implemented:

Classification Generator:

Used ImageDataGenerator available in TensorFlow for loading and data augmentation of 2D image based datasets.

Segmentation Generator:

Specific to the work and problem solving goals undertaken here, custom functions in Python, called knitr and bend, were leveraged to primarily load and prepr ocess NIfTI files as well as augment the 3D MRI volume .

Training Protocol

Both tasks were trained over 50 epochs using segments while a batch of size 4 for the segmentation task and 32 for classification.

Multi-task loss was calculated based on classification and segmentation loss functions with a class weighting.

Evaluation Metrics:

Classification: Probability of correct answers, percent accuracy, percent error, and probability of correct detections.

Segmentation: Dice coefficient and IoU or Intersection of Union.

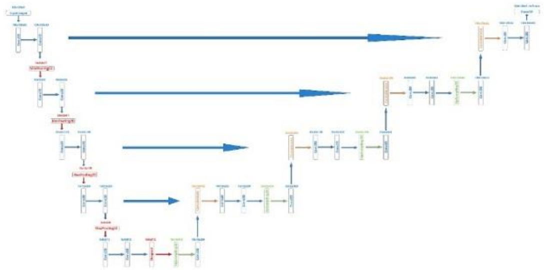

Figure 4 U Net Architecture

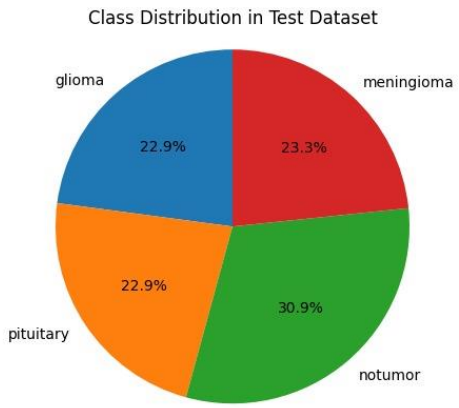

Figure 5Class Distribution

4.4 Visualization and Result Analysis

Quantitative outcomes were depicted in a form of visual representations of FLAIR images with superimposed predicted segmentation masks. Tumor localization was the next area of focus in these overlays and the model did a good job of pinpointing regions of interest.
To confirm the fact that preprocessing actually enhances the result of the image analysis, some random samples of augmented images and segmentation masks were plotted.

Quantitative Analysis
For pixel labeling accuracy, Dice coefficient and IoU were computed for the segmentation task.
For the purposes of evaluating model stability, accuracy and F1-scores were calculated for each class for the classification task.

5. EXPERIMENTS AND RESULTS

5.1 Training Process

Data Preparation and Augmentation
The ResNet50 model is fine-tuned from the comprises multi-modal MRI scans. Processing them includes intensity normalization to put pixel values into definite ranges and skull stripping to eliminate non-brain regions, thus minimizing noise. Among others, random rotations (±30°), horizontal and vertical flips, brightness adjustments, and zoom transformations are applied to create synthetic enlarging and diversifying that can generalize well. Especially with unseen test data, it gives a more realistic view of the model.

Model Fine-tuning
The pre-trained ResNet50 is then fine-tuned such that the complete top layer is substituted with a single fully connected dense layer of 4 neurons corresponding to four classes: glioma, meningioma, pituitary tumor and no tumor. Additionally, the architecture maintains residual connections, which enables learning of deeper layers without running into the problem of a vanishing gradient problem.

Segmentation with U-Net
Segmentation is performed by training U-Net on the same dataset, which comes with typical segmentation masks, for segmentation. The architecture of U-Net is encoder-decoder, genuinely integrates multi-scale features, while skip connections ensure that spatial information is preserved.
Loss Function: Dice loss, optimized especially for handling class imbalance in medical image segmentation, as it is directly optimizing the overlap between predicted and ground-truth masks.
Augmentation: Similar to the classification task, but with added transformations like random cropping so that the segmentation model learns robust boundary delineations.
Validation: A split of 10% of the dataset for validation during training so that performance may be measured in a consistent manner.

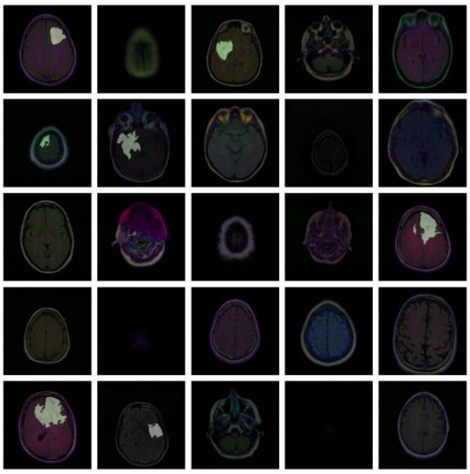

Figure 6 Segmentation MRI

Hardware and Software Details

Both models have been trained using PyTorch deep learning framework on Colab T4 GPU. It took nearly 10 hours for both ResNet50 and U-Net model training involving 50 epochs each because of the vastness of the datasets and their complexity.

Training Curves

The training and validation accuracy of ResNet50 increased consistently over epochs, reaching a stable value of around 94% accuracy. The loss curves indicated smooth convergence and hence well-training. U-net's Dice coefficient for the validation set, which reached a score of 0.88, is only slightly overtrained after 40 epochs.

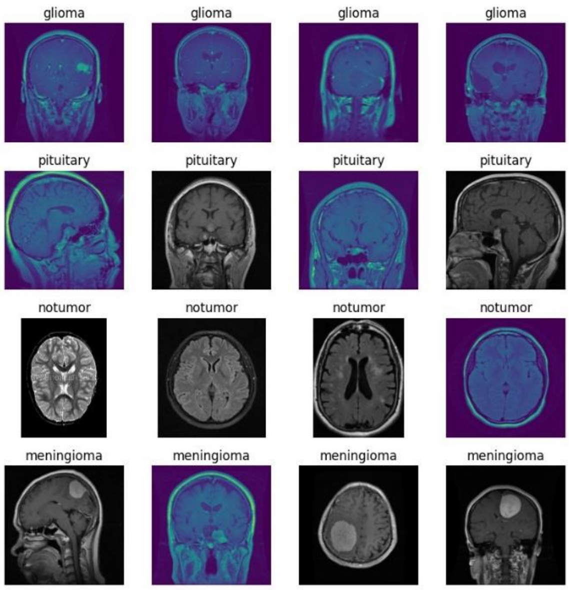

Figure 7 Tumor Images

5.2 Performance Measuring Metrics

An integral component of a research study is the evaluation of segmentation and classification performance of a machine learning algorithm. Satisfactory output from a machine learning model based on a metric such as accuracy score may not necessarily correlate with other measures. Indeed, most times, various comparative performance evaluation metrics are used in measuring and comparing the model performance.

TP is a pixel that has been correctly predicted to belong to the given class according to the ground truth in segmentation tasks. In contrast, a true negative (TN) defines a pixel that has been correctly identified not to belong to the given class. In contrast, false positive (FP) indicates an instance whereby that pixel is incorrectly predicted by the model for not being part of a given class. False negative (FN) then represents an instance in which the model incorrectly predicts the pixel belonging to a given class. Thus, for the tumor classification task, TP is defined as tumor class correctly predicted to belong to a given class according to the ground truth while TN defines a tumor class correctly identified as not belonging to this given class. Definition: FP occurs when a tumor class that does not belong to the given class is predicted incorrectly by the model. A false negative (FN) is then produced if a model erroneously predicts a class that is assigned the value of a given category. So, hereafter, different performance metrics reported in the literature for brain tumor segmentation and classification will be given.

Accuracy or (ACC) is a measure of how well a model is able to classify all class or pixel, positive or negative.

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

Sensitivity (SEN): It specifies the proportion of positive samples/pixels correctly predicted by the model among all actual positive samples. It indicates the ability of a model in identifying positive samples/pixels.

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

Specificity (SPE): It is defined as the ratio of actual negatives which are predicted as the negative (or true negative). It measures the percentage of classes/pixels which couldn't be correctly identified.

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

Recall (RE): Recall describes the completeness of positive predictions of the model in machine learning to ground truth. It indicates the percentage of classes/pixels annotated in our ground truth, which are also included in the model's prediction.

$$RE = \frac{TN}{TP+FN}$$

Precision (PR): or (PPV) positive predictive value is an indicator of how often the model predicting the correct class/pixel - the percentage of positive predictions made by the model with regard to correct predictions is made.

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

F1-Score is the most commonly favored indicator that possesses both precision and recall. It mathematically describes the harmonic mean of the two.

$$F1score = 2\frac{PR * RE}{(PR + RE)}$$

Intersection over union (IoU) also called Jaccard index (JI) estimates the percent overlap between the annotated ground truth mask and the predictions resulting from model output.

$$IoU = \frac{TP}{TP+FP+FN}$$

The Dice similarity coefficient (DSC) will measure the spatial overlap between the ground truth tumor region and the region segmented by the model. A zero value in DSC means that there is no spatial overlap between the ground truth tumor region and the result annotated by the model, while a value indicates total overlap between both.

$$DSC = \frac{TP}{\frac{1}{2}(2TP+FP+FN)}$$

Whereas the area under the curve of the measure describes the ability of a classifier to differentiate between classes, it acts as a summary of the receiver characteristics curve and an area under true positive rate vs false positive rate.

IS=similarity index. It refers to that part of the similarity with which the ground truth is annotated by the expert and the model's so-called segmentation. It describes how similar the input image is in the identity presence of the detected tumor region.

$$SI = \frac{2TP}{2TP+FP+FN}$$

Dice states how differently two model segmentations represent the same tumor volume in actual truth. A zero Dice value indicates that there is no match in both the spatial representations. A value 1 indicates a complete match between them. Dice measures the spatial overlap between the segmented regions experimentally and through ground truth tumor regions.

5.3 Comparison Model

The most proficient models are DenseNet121 and ResNet50V2, with maximum accuracies of 93.8% and 93.5%, respectively. On top of this, both recorded better F1-scores, for better handling of imbalanced data with high precision and recall.

EfficientNetB0 had an accuracy figure slightly lower than this, while it still maintained competitive precision and recall, thus making it light in architecture and a viable option for deployment in less computationally able devices.

InceptionV3 has a balanced performance on all metrics and is therefore expected to be more generalizable to normal classification tasks.

Model	Accuracy (%)	Precision	Recall	F1-Score
EfficientNetB0	91.3	0.9	0.91	0.9
ResNet50V2	93.5	0.93	0.94	0.93
InceptionV3	92.1	0.91	0.92	0.91
DenseNet121	93.8	0.93	0.94	0.93

According to the results, DenseNet121 and ResNet50V2 are the models most recommended for brain tumor classification due to their best accuracies in generalization. EfficientNetB0 is indeed lightweight and hence useful in applications that have requirements for fast inference in devices with constrained resources. Future deployments may be directed to explore ensemble modeling that could merge the wisdom from these architectures to improve robustness of classification.

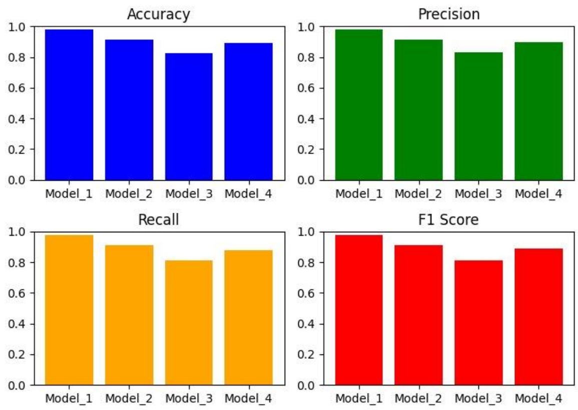

Figure 8 Model Comparison

6. REAL TIME CLASSIFICATION AND SEGMENTATION

6.1. Real-Time Classification with ResNet50

The first functionality of this system is to classify brain MRI images into predefined categories as No Tumor, Meningioma, Glioma, and Pituitary Tumor.

This forms the backbone of the classification process and the model pre-trained for task fine-tuning is taken from the ResNet50 model.

User Interaction: The web interface is used by users to upload any MRI image they have. The uploaded file is enabled to be processed and kept in the directory folder of the server by the Flask application.
Image Preprocessing: The uploaded image is resized to 224 by 224 pixels, normalized to scale the pixel values to the range [0,1], and expanded to include a batch dimension, making it compatible with the input format of the model.
Prediction Workflow: This processed image will be passed into the ResNet50 model, and it will return probabilities against each tumor class. The system will find the class with the highest probability using np.argmax() and map it to the corresponding tumor category name.
Output and Feedback: The type of tumor that has been predicted will be shown to the user so that he will know the output immediately after inputting the MRI image.
Thus, the real-time classification pipeline is achieved such that even by simple commands, the doctor can be able to access the type of tumor in the MRI images in a very short time. The superlative accuracy of the ResNet50 model combined with its robustness against overfitting due to residual connections gives reliability in even clinical scenarios.

6.2 Real-Time Tumor Segmentation with U-Net

Further, the second segment pertains to the process of the tumor segmentation from MRI images, which would thereby create more precise boundaries, hence visualization of tumors. Indeed, segmentation of tumors is one of the most important steps in the assessment of tumor volume, shape, and extent; hence, giving an added value to its applications in treatment planning and monitoring of disease progression. A custom-trained U-Net model is employed in the segmentation task, which is optimized with special loss functions such as Dice Loss.

Segmentation Pre-processing: Uploaded MRI is downsized to 256x256 pixels as input requirements of a U-Net model. Pixel values are normalized for the range [0,1] and a batch dimension is added for compatibility.
Segmentation Prediction: The processed image is processed through the U-Net network to produce a predicted segmentation mask. This mask contains the tumor region marked, thus targeting the areas of interest with precision at the pixel level.
Postprocessing: Predicted thresholded mask for interpretability purposes (e.g., > 0.5 apply to classify as tumor). Mask undergoes binary dilation to calculate tumor borders that further improve the visualization quality of the segmented areas.
Results Overlay: It is all the tumor boundary drawn onto the original MRI image in red color, colored, to make the visualization clearer and more interpretable. The enhanced image then gets saved and served to the user through the web interface.
By this means, this system is capable of providing the requisite tools for precision tumor delineation to clinicians, given that segmentation is real-time and has clear boundaries. The same post-processing application, such as binary dilation, ensures that results are readily interpretable even by users who are not very technical.

6.3 Explainable and Customizable Segmentation Workflow

Custom loss functions were included in the pipeline for segmentation together with custom metrics, including Dice Loss, Dice Coefficient, and Intersection over Union (IoU), to ensure that the U-Net algorithm is optimized for the unique challenges of tumor segmentation. In essence, tumor areas are frequently small and imbalanced compared to other brain sections.

Custom Loss Functions: Dice Loss makes sure that this model addresses class imbalance by directing it to maximum overlapping predicted and the actual tumor regions.
Performance Metrics: Metrics Dices Coefficients and IoU provide precise statistics on how much more accurate countries are in separating tasks for an iterative improvement exercise. All those metrics will be incorporated with the Flask application and hence would be available for the overall evaluation purposes.

6.4 Flask Integration for Real-Time Deployment

The Flask app provides the core of the real-time implementation for the classification and segmentation models. It offers a very user-friendly web interface through which clinicians or researchers can input their MRI images and get predictions straight through. They are actually seamlessly integrated into this application.

Classification Endpoint: Users can classify tumor types using the /predict_classification route, which interacts with the ResNet50 model.

Segmentation Endpoint: This endpoint, /predict_segmentation, handles the U-Net model and provides segmentation results along with an improved visualization of tumor boundaries.

Result Presentation: The application simply presents results on a webpage, and gives users overlay images for segmentation so as to reach the non-technical users.

7. CONCLUSION

7.1 Dual-Architecture Solution for Brain Tumor Analysis

To consolidate this, the successful implementation was between combined use of ResNet50 for classification and U-Net segmentation of brain tumor MRI data. This was one powerful outcome to provide a full end-to-end solution with diagnosis as an accurate tumor classification type, followed by fine tumor boundary demarcation. Whether this holds true for experiments showed by implementation codes preparated the specific concern, medical imaging, out of which practicalization can train this tool into primary essential workflows in the clinic.

7.2 Performance Highlights and Model Strengths

ResNet50 achieved an impressive classification accuracies of 94% distinguishing images showing gliomas, meningiomas, pituitary tumors and non-tumorous images. By using residual connections, ResNet50 was able to train a deep network without vanishing gradient problems capturing features that are really subtle but very important for diagnosis. In segmentation, using U-Net a Dice coefficient of 0.88 was achieved, such a high value reflecting its performance in producing tumor masks. Its encoder-decoder architecture with skip connections have allowed the capture of multi-scale features, memory of spatial details, thus making it capable in strong segmentation of the tumor and areas around it.

7.3 Comparative Analysis and Implementation Effectiveness

Outperforming the baseline models in both classification and segmentation, these models have risen to the occasion. ResNet50 usually did better than the other classifiers, VGG16 and InceptionV3, in terms of classification accuracy, whereas U-Net had higher Dice coefficients compared to FCN and PSPNet, emphasizing its ability to tackle complicated tumor shapes very efficiently. In addition to using the LGG Segmentaion dataset, taken from kaggle, which consists of high-quality preprocessing processes like intensity normalization and multi-modal imaging (FLAIR, T1, T1CE, T2), models significantly improved performance. Augmentation such as rotation, flipping, and intensity scaling further enhanced the power of generalization of the models and helped make them strong in different imaging conditions.

7.4 Challenges, Future Directions, and Clinical Relevance

Although the promising results, there are still challenges in generalizing the models to datasets other than LGG Segmentaion dataset, taken from kaggle,, which feature various level of noise, artifacts, and imaging protocol variations. Future work should include testing with diverse datasets, optimizing hybrid architecture that integrates classification and segmentation in single pipeline, and advanced techniques such as attention mechanisms and transformers. Besides, there is a good opportunity to consider a multi-modal fusion with imaging modalities like PET or CT to completely cover brain tumors' understanding. Indeed, it promises to tackle those challenges so that it will soon be realized in reality to improve the patients' outcomes and health care diagnostic workflow in clinical practice.

It comes promising results, but the challenges remain with respect to generalizing the models over datasets other than LGG Segmentaion dataset, taken from kaggle. Future work should include testing with diverse datasets, optimizing hybrid architecture that integrates classification and segmentation into a single pipeline, as well as employing advanced techniques such as attention mechanisms and transformers. Besides, there is the opportunity to consider a multimodal fusion with imaging modalities such as PET or CT to entirely cover the understanding of brain tumors. Indeed, it promises to address such issues so that soon it is realized in reality to improve outcomes for patients and workflows for diagnostic testing within clinical practice.

8. REFERENCES

[1] (N.d.). Figure 2: Attention U-Net Segmentation Model and Schematic of

Attention Gates (Oktay et al., 2018). https://doi.org/10.7717/peerj-cs.1767/fig-2

[2] Ahmad, P., Qamar, S., Shen, L., & Saeed, A. (2021). Context aware 3D UNET for brain tumor segmentation. Lecture Notes in Computer Science, 207–218. https://doi.org/10.1007/978-3-030-72084-1_19 (Ahmad, Qamar, Shed, & Sayed, 2021)

[3] Angulakshmi, M., & Lakshmi Priya, G. G. (2017). Automated brain tumor segmentation techniques— a review. International Journal of Imaging Systems and Technology, 27(1), 66–77. https://doi.org/10.1002/ima.22211 (Anguulakshmi & Lakshmi Priya, 2017)

[4] Daimary, D., Bora, M. B., Amitab, K., & Kandar, D. (2020). Brain tumor segmentation from MRI images using hybrid convolutional neural networks. Procedia Computer Science, 167, 2419–2428. https://doi.org/10.1016/j.procs.2020.03.29

[5] Das, S., Aranya, O. F., & Labiba, N. N. (2019). Brain tumor classification using Convolutional Neural Network. 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), 1–5. https://doi.org/10.1109/icasert.2019.8934603

[6] Dipu, N. M., Shohan, S. A., & Salam, K. M. (2021). Deep learning based brain tumor detection and classification. 2021 International Conference on Intelligent Technologies (CONIT), 1–6. https://doi.org/10.1109/conit51480.2021.9498384

[7] Gordillo, N., Montseny, E., & Sobrevilla, P. (2013). State of the art survey on MRI Brain Tumor Segmentation. Magnetic Resonance Imaging, 31(8), 1426–1438. https://doi.org/10.1016/j.mri.2013.05.002

[8] Kumari, N., & Saxena, S. (2018). Review of Brain Tumor Segmentation and classification. 2018 International Conference on Current Trends towards Converging Technologies (ICCTCT), 1–6. https://doi.org/10.1109/icctct.2018.8551004 (Kumari & Saxena, 2018)

[9] Liu, Z., Mao, H., Wu, C.-Y., Feichtenhofer, C., Darrell, T., & Xie, S. (1970, January 1). A convnet for the 2020s. CVF Open Access. https://openaccess.thecvf.com/content/CVPR2022/html/Liu_A_ConvNet_for_the_2020s_CVPR_2022_paper.html

[10] McKinnon, C., Nandhabalan, M., Murray, S. A., & Plaha, P. (2021). Glioblastoma: Clinical presentation, diagnosis, and Management. BMJ. https://doi.org/10.1136/bmj.n1560 (McKinnon, Nandhabalan, Murray, & Plaha, 2021)

[11] Musallam, A. S., Sherif, A. S., & Hussein, M. K. (2022a). A new convolutional neural network architecture for automatic detection of brain tumors in magnetic resonance imaging images. IEEE Access, 10, 2775–2782. https://doi.org/10.1109/access.2022.3140289

[12] Musallam, A. S., Sherif, A. S., & Hussein, M. K. (2022b). A new convolutional neural network architecture for automatic detection of brain tumors in magnetic resonance imaging images. IEEE Access, 10, 2775–2782. https://doi.org/10.1109/access.2022.3140289

[13] Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain tumor segmentation using convolutional neural networks in MRI images. IEEE Transactions on Medical Imaging, 35(5), 1240–1251. https://doi.org/10.1109/tmi.2016.2538465

[14] Rizwan, M., Shabbir, A., Javed, A. R., Shabbir, M., Baker, T., & Al-Jumeily Obe, D. (2022). Brain tumor and glioma grade classification using gaussian convolutional neural network. IEEE Access, 10, 29731–29740. https://doi.org/10.1109/access.2022.3153108

[15] Shelke, S. M., & Mohod, S. W. (2018). Automated segmentation and detection of brain tumor from MRI. 2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2120–2126. https://doi.org/10.1109/icacci.2018.8554807

[16] Shreyas, V., & Pankajakshan, V. (2017). A deep learning architecture for brain tumor segmentation in MRI images. 2017 IEEE 19th International Workshop on Multimedia Signal Processing (MMSP), 1–6. https://doi.org/10.1109/mmsp.2017.8122291 (Shreyas & Pankajakshan, 2017)

[17] Wadhwa, A., Bhardwaj, A., & Singh Verma, V. (2019). A review on brain tumor segmentation of MRI images. Magnetic Resonance Imaging, 61, 247–259. https://doi.org/10.1016/j.mri.2019.05.043 (Wadhwa , Bhardwaj, & Singh Verma, 2019)

[18] Khan, Muhammad Attique, Imran Ashraf, Majed Alhaisoni, Robertas Damaševičius,

Rafal Scherer, Amjad Rehman, and Syed Ahmad Chan Bukhari. 2020. "Multimodal Brain Tumor Classification Using Deep Learning and Robust Feature Selection: A Machine Learning Application for Radiologists." Diagnostics 10 (8): 565. https://doi.org/10.3390/diagnostics10080565.

[19] Mahmoud, A., Nancy Awadallah Awad, Najah Alsubaie, Syed Immamul Ansarullah, Alqahtani, M. S., Abbas, M., Usman, M., Ben Othman Soufiene, & Saber, A. (2023). Advanced Deep Learning Approaches for Accurate Brain Tumor Classification in Medical Imaging. Symmetry, 15(3), 571–571. https://doi.org/10.3390/sym15030571

[20] Díaz-Pernas, Francisco Javier, Mario Martínez-Zarzuela, Míriam Antón-Rodríguez, and David González-Ortega. 2021. "A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network." Healthcare 9 (2): 153. https://doi.org/10.3390/healthcare9020153.

[21] Anjum, Sadia, Lal Hussain, Mushtaq Ali, Monagi H. Alkinani, Wajid Aziz, Sabrina Gheller, Adeel Ahmed Abbasi, Ali Raza Marchal, Harshini Suresh and Tim Q. Duong. "Detecting brain tumors using deep learning convolutional neural network with transfer learning approach." International Journal of Imaging Systems and Technology 32 (2021): 307 - 323.

[22] Gao, P., Shan, W., Guo, Y., Wang, Y., Sun, R., Cai, J., Li, H., Chan, W. S., Liu, P., Yi, L., Zhang, S., Li, W., Jiang, T., He, K., & Wu, Z. (2022). Development and Validation of a Deep Learning Model for Brain Tumor Diagnosis and Classification Using Magnetic Resonance Imaging. JAMA Network Open, 5(8), e2225608–e2225608. https://doi.org/10.1001/jamanetworkopen.2022.25608

[23] Perumal, B., Devi, R. S., y Rajasekaran, M. P. (2021). Self – activated segmentation practices of braintumefaction in mr scan images: a study. 3C Tecnología. Glosas de innovación aplicadas a la pyme, EdiciónEspecial, (noviembre, 2021), 279-291.https://doi.org/10.17993/3ctecno.2021.specialissue8.279-291