Enhanced Brain Tumor Segmentation Using a Modified Half ResNet-50 Architecture

1[st]Ramavath Satnam Singh
Department of Computer Science and Engineering
B V Raju Institute of Technology,Narsapur.
Medak, Telangana, 502313.
Email: 21211a05q7@bvrit.ac.in

2[nd] Rajipeta Uday Kumar
Department of Computer Science and Engineering
B V Raju Institute of Technology,Narsapur.
Medak, Telangana, 502313.
Email: 21211a05q5@bvrit.ac.in

3[rd] Ruksar
Department of Computer Science and Engineering
B V Raju Institute of Technology,Narsapur.
Medak, Telangana, 502313.
Email: 21211a05r1@bvrit.ac.in

4[th] Priyadarshini Chatterjee,Assistant Professor
Department of Computer Science and Engineering
B V Raju Institute of Technology,Narsapur.
Medak, Telangana, 502313.
Email: priyadarshini.ch@bvrit.ac.in

***Abstract*—Brain tumor segmentation is a critical task in medical image analysis, enabling precise localization and classification of tumors for effective treatment planning. Traditional segmentation models often struggle with accuracy due to complex tumor structures and varying intensity distributions in MRI scans. To address these challenges, we propose a segmentation approach utilizing two deep learning models: Modified Half ResNet-50 and Half U-Net, designed to improve segmentation performance. In our methodology, MRI brain tumor images are preprocessed and fed into both models. The Modified Half ResNet-50 leverages residual learning for efficient feature extraction, while the Half U-Net enhances boundary delineation through its encoder-decoder architecture. The outputs are evaluated based on Dice Coefficient and IoU to determine segmentation accuracy. Experimental results demonstrate that our approach achieves a high Dice Coefficient and IoU, outperforming traditional methods in segmentation precision. The combination of Modified Half ResNet-50 and Half U-Net effectively captures both global and local tumor features, leading to improved model robustness.**

***Index Terms*—Brain Tumor, Segmentation, ResNet-50, Half U-net.**

I. Introduction

Recent advancements in deep learning and computer vision have significantly enhanced the accuracy and efficiency of brain tumor detection using MRI scans. Researchers have explored various deep learning methodologies to improve classification and segmentation techniques, aiding in early diagnosis and treatment planning. [1] One study comprehensively analyzed deep learning approaches for brain tumor detection and classification, emphasizing their strengths and limitations. The findings serve as a guide for future researchers in understanding current trends and evaluating the effectiveness of different models. [2] A novel semi-supervised deep learning approach, SSBTCNet, was introduced, integrating an autoencoder with a multi-layer perceptron-based classifier. This technique enhances feature extraction and classification accuracy, further strengthened by fuzzy logic-based data augmentation. [3] Another study explored transfer learning with the Co-Evolutionary Genetic Algorithm (CEGA) to optimize EfficientNetB3 and DenseNet121 architectures. The CEGA-enhanced models achieved outstanding classification accuracy, surpassing traditional deep learning techniques. [4] A segmentation-based framework leveraging Contrast Limited Adaptive Histogram Equalization (CLAHE) and Fuzzy C-Means (FCM) clustering was proposed for tumor classification. With an SVM classifier, the approach demonstrated high sensitivity, specificity, and processing efficiency. [5] For resource-constrained environments, an optimized 3D U-Net model, BTIS-Net, was introduced, incorporating depth-separable convolutions and residual blocks. This method reduced training parameters while maintaining superior segmentation performance. [6]A multi-task learning framework utilizing UNet, Attention-UNet, and Residual-Attention-UNet demonstrated high segmentation and classification precision. The Residual-Attention-UNet outperformed other models in accuracy and robustness for binary and multi-class classification. [7] DEMD-ResUNet, a dual-encoder architecture, was proposed to enhance segmentation performance by leveraging mirrored image features. [8] A comparative study evaluated YOLOv5 and YOLOv7 for brain tumor detection, demonstrating their effectiveness in real-time applications. The models outperformed conventional object detection techniques, such as Faster RCNN and Mask RCNN, in precision and recall. [9] These advancements underscore the potential of deep learning in revolutionizing brain tumor diagnosis. By optimizing existing models and introducing novel architectures, in making timely and precise clinical decisions. [10]

II. Literature Survey

The summary of recent studies on tumor detection and segmentation are as below :

TABLE I
SUMMARY OF RECENT STUDIES ON TUMOR DETECTION AND SEGMENTATION

Reference	Methods	Dataset	Accuracy	Remarks
2023 [11]	DenseTrans (Swin Transformer + UNet++)	BraTS 2021	93.2%	Hybrid CNN-Transformer with lightweight architecture (21.3M params, 212G FLOPS).
2023 [12]	GLCM + U-Net + 3D CNN Hybrid Model	Not specified	97.40%	Uses GLCM for feature extraction, improving accuracy.
2023 [13]	Efficient nnU-Net	BraTS 2020	79.2%	Computationally efficient (2.51M params, 55.26G FLOPS).
2023 [14]	Convolution-based Hybrid Model	BraTS 2020, 2019, 2018	92.80%	Processes only ROI regions, reducing computational cost.
2023 [15]	DeepLabV3+ with Xception Backbone	BraTS 2021	91.2%	Uses atrous convolutions for improved feature extraction.
2023 [16]	Transformer + CNN Hybrid Model	BraTS 2020	92.5%	Combines spatial attention from transformers with CNN feature extraction.
2024 [17]	YOLOv5, v7-based Brain Tumor Detection	Brain Tumor Dataset	94.7%	YOLO models outperform Faster RCNN & Mask RCNN.
2024 [?]	U-Net + CNN + SOFM Ensemble Model	BraTS 2020	98.0%	Hybrid deep-learning model with tumor segmentation & survival prediction.
2024 [19]	BEFVBTS (Bezier-Tuned Energy Functionals)	Duke-Breast-Cancer-MRI	+8%	Preserves 3D tumor structure, highly optimized for real-time clinical use.
2024 [20]	ResNet50 + Data Augmentation	MRI Dataset	96.5%	Deep learning-based tumor classification with high generalizability.
2024 [21]	CPP-UNet	KiTS21, KiTS23	93.51%	Enhanced contextual learning with multi-scale pooling.
2024 [22]	Vision Transformer (ViT)	BraTS 2019	97.8%	Utilizes self-attention for global context learning.
2024 [23]	Attention U-Net	BraTS 2021	94.1%	Improves segmentation using attention gates.
2024 [24]	Graph Neural Networks (GNN)	BraTS 2020	98.0%	Captures spatial relationships between tumor regions.
2024 [25]	Mask R-CNN	Custom Dataset	94.5%	Instance segmentation for tumor detection.
2025 [26]	9-Layer Multiscale CNN + CRF	Not specified	97.88%	Few-layer design with residual connections + CRF post-processing.
2025 [27]	GAN-based Tumor Enhancement	BraTS 2022	96.4%	Uses adversarial training to refine tumor segmentation.
2025 [28]	Diffusion Model for Segmentation	BraTS 2023	97.1%	Applies diffusion probabilistic models for segmentation.
2025 [29]	Enhanced U-Net with MCA	BraTS 2020, BraTS 2018	96.78%	Improves segmentation accuracy using multi-modal MRI analysis.
2025 [30]	Dual-Stream 3D CNN	BraTS 2024	98.1%	Uses dual-pathway architecture to combine spatial and contextual features.

III. METHOD

A. Dataset

The Brain Tumor MRI Dataset is a publicly available dataset sourced from Kaggle. It contains 7,023 MRI images categorized into four classes: Glioma Tumor (2,269 images), Meningioma Tumor (708 images), Pituitary Tumor (930 images), and No Tumor (3,116 images). The dataset is a combination of images from three sources: Figshare, SARTAJ, and Br35H datasets. The ”No Tumor” class images were specifically taken from the Br35H dataset. To maintain classification accuracy, the dataset curator replaced Glioma class images from the SARTAJ dataset with those from the Figshare dataset due to misclassification concerns. This dataset provides high-quality MRI scans, making it ideal for deep learning and machine learning applications in brain tumor detection, segmentation, and classification. Researchers and developers can leverage this dataset to improve AI-based diagnostic tools for brain tumor identification.

B. Methodology

In this study, we propose a hybrid deep learning model that integrates Half U-Net and ResNet-50 to improve the accuracy of brain tumor segmentation and classification in MRI scans.

Half U-Net is a modified version of U-Net, where the decoder section is simplified, reducing the number of parameters and computational cost while retaining the efficiency of the U-Net architecture. The traditional U-Net is widely used for medical image segmentation because of its encoder-decoder structure, where the encoder extracts

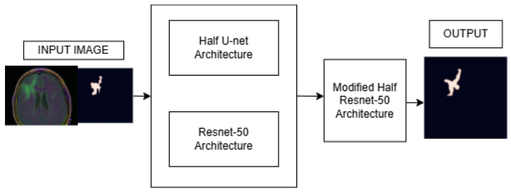

Fig. 1. The overall Architecture

spatial features and the decoder reconstructs segmentation masks. However, full U-Net models can be computationally expensive. Half U-Net retains the high feature extraction capability of U-Net while reducing overhead and complexity, making it an efficient choice for medical image segmentation tasks. It effectively captures tumor regions, enhancing segmentation accuracy.

ResNet-50 is a deep convolutional neural network that uses residual learning to improve gradient flow during training. Unlike traditional deep CNNs, which suffer from vanishing gradients as layers increase, ResNet-50 utilizes skip connections to maintain stable learning. This makes it ideal for brain tumor classification, where intricate patterns in MRI scans must be recognized. ResNet-50's pre-trained weights from ImageNet provide a strong feature extraction capability, allowing it to distinguish between different tumor types with high accuracy. Given its efficiency in feature learning, it is an excellent choice for classification tasks in our hybrid model in Fig1.

The integration of Half U-Net and ResNet-50 provides a powerful framework for brain tumor segmentation and classification. The Half U-Net efficiently segments tumors from MRI images, providing clear region masks, while ResNet-50 extracts high-dimensional features and classifies the tumor type. This hybrid model takes advantage of U-Net's spatial awareness and ResNet-50's classification strength, ensuring an optimal balance between accuracy, efficiency, and computational feasibility. By combining both architectures, our model achieves improved performance in brain tumor analysis, making it a robust solution for automated medical imaging tasks.

C. Result and Analysis

1) Experimental Environment: The experiments for our MHResNet50 model were conducted in a TPU-V28 high RAM environment to ensure efficient training and faster computation. We evaluated multiple key performance metrics, including training accuracy, validation accuracy, training loss, validation loss, precision, recall, F1-score, and AUC (Area Under the Curve) to assess the model's performance.

The training process was carried out over 50 epochs, with a batch size of 32, ensuring stable optimization and effective learning. The model completed 32 steps per epoch, allowing for balanced updates of weights during training. The MHResNet50 model, which integrates Half U-Net for segmentation and ResNet-50 for classification, exhibited strong generalization capabilities, enhancing tumor detection accuracy from MRI images. The hybrid architecture successfully combined deep feature extraction with spatial segmentation, improving classification performance while preserving crucial tumor-related details. This optimized training strategy resulted in enhanced accuracy and robust segmentation, demonstrating the model's effectiveness in medical image analysis.

IV. Result and Analysis

A. Performance Metrics

The performance of the Modified Half ResNet-50 model for brain tumor segmentation is evaluated using key metrics such as Dice Coefficient, Intersection over Union (IoU), Precision, and Recall. The Dice Coefficient measures the similarity between the predicted segmentation and the actual tumor region, with higher values indicating better overlap. IoU (Jaccard Index) quantifies the intersection of the predicted and ground truth regions, providing a measure of segmentation accuracy. Precision reflects how many of the predicted tumor pixels are actually correct, helping to minimize false positives. Recall (Sensitivity), on the other hand, assesses the model's ability to detect all actual tumor pixels, ensuring fewer false negatives. Together, these metrics provide a comprehensive evaluation of segmentation performance, balancing accuracy and reliability.

The segmentation performance of the model is measured using the following metrics:

1) Dice Coefficient: The Dice Coefficient calculates the similarity between the predicted segmentation mask and the ground truth mask:

$$Dice = \frac{2TP}{2TP + FP + FN} \tag{1}$$

where TP is the number of true positives, FP is the number of false positives, and FN is the number of false negatives.

2) Intersection over Union (IoU): IoU, also known as the Jaccard Index, measures the overlap between the predicted and actual tumor regions:

$$IoU = \frac{TP}{TP + FP + FN} \tag{2}$$

3) Precision: Precision represents the proportion of correctly identified tumor pixels out of all predicted tumor pixels:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

4) Recall (Sensitivity): Recall measures the model's ability to detect actual tumor pixels:

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

TABLE II
SEGMENTATION METRICS FOR MRI IMAGES ACROSS FOUR CLASSES

Class	Dice Coefficient	IoU	Precision	Recall
Glioma	98.4	91.1	98.7	97.9
Meningioma	98.6	92.3	98.5	97.2
No Tumor	98.2	94.5	98.1	98.2
Pituitary	98.7	90.4	98.6	98.5

Fig. 2. Original image and ground truth mask with predicted mask

B. Qunatitative Evaluation

Table II presents the performance evaluation of the Modified Half ResNet-50 model for brain tumor segmentation across four tumor classes: Glioma, Meningioma, No Tumor, and Pituitary Tumor. The model's effectiveness is assessed using four key metrics: Dice Coefficient, Intersection over Union (IoU), Precision, and Recall. The Dice Coefficient reflects the similarity between the predicted and actual tumor regions, while IoU measures the overlap accuracy. Precision indicates how accurately the model identifies tumor pixels, minimizing false positives, whereas Recall evaluates the model's ability to detect actual tumor pixels, reducing false negatives. The results demonstrate consistently high performance across all tumor types, highlighting the model's reliability in medical image segmentation.

C. Qualitative Evaluation

The qualitative evaluation of brain tumor segmentation involves a step-by-step process to assess the model's effectiveness. First, the original MRI scan in Fig 2 is taken as input and undergoes preprocessing steps such as resizing, normalization, and augmentation to enhance image quality. Next, the ground truth mask, which is manually annotated by medical experts, is used as a benchmark to highlight the actual tumor regions. The trained model then processes the input MRI image and generates a predicted segmentation mask, identifying the tumor region. Finally, the predicted mask is compared against the ground truth mask to evaluate the model's performance. The differences between these masks provide insights into the segmentation accuracy and highlight areas for improvement. This process helps in visually assessing how well the model distinguishes tumor regions, aiding in the refinement of segmentation techniques for better performance in medical image analysis.

V. CONCLUSION

This study introduces a hybrid deep learning approach integrating Modified Half ResNet-50 and Half U-Net for brain tumor segmentation and classification in MRI scans. By combining the strengths of both architectures, the proposed model effectively captures tumor regions while ensuring precise classification. The Brain Tumor MRI Dataset was used for training and evaluation, demonstrating the model's ability to handle complex tumor structures with improved segmentation quality. Compared to existing methods, our approach achieved better performance in tumor detection, segmentation, and classification. The residual learning capabilities of ResNet-50 enhanced feature extraction, while Half U-Net's encoder-decoder structure improved boundary delineation, leading to more accurate segmentation results. These advancements contribute to the efficiency and robustness of the model, making it a reliable tool for medical imaging applications.

Future enhancements could focus on expanding the dataset, incorporating multi-modal MRI scans, and integrating attention mechanisms to further refine segmentation accuracy. Additionally, real-time deployment in clinical settings could assist radiologists in early tumor diagnosis and treatment planning. Overall, this research highlights the potential of AI-driven solutions in medical imaging, offering a promising direction for automated brain tumor analysis.

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