ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

# COMPREHENSIVE BRAIN TUMOR SEGMENTATION APPROACHES WITH MULTIMODAL IMAGE FUSION TECHNIQUES USING CNN

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**Abstract**
Accurate segmentation of brain tumors from medical imaging data is crucial for diagnosis , treatment planning and monitoring of brain tumor patients. This research explores the application of convolutional neural networks (CNNs) for brain tumor segmentation , focusing on the integration of multimodal imaging techniques. Specifically , we investigate the fusion of various imaging modalities such as Magnetic Resonance Imaging (MRI) and CT scans (Computed Tomography) to improve segmentation accuracy and robustness. Our approach involves preprocessing techniques for data normalization and augmentation, followed by the design & training of CNN architectures tailored for multimodal image fusion. Evaluation metrics include Dice coefficient , sensitivity and specificity , comparing our method with traditional single modality segmentation approaches. This study conducts a comparative exploration of CNN model, including HRnet, U-net and ResUnet architectures. Experimental results demonstrate that our approach of multimodal image fusion using CNN achieves superior segmentation performance, effectively handling variations in tumor appearances across different imaging modalities. Experimental results on real-world data demonstrates that our approach of multimodal image fusion using Deep Neural Networks achieves superior segmentation performance, with accuracies of 99.49% for HRNet, 98.10% for ResUNet, and 99.48% for UNet, effectively handling variations in tumor appearances across different imaging modalities. This research contributes to advancing state-of-the-art in brain tumor segmentation, offering a comprehensive framework that can potentially enhance clinical decision-making and patient care.
**Keywords** - MRI, CT, CNN, ResUnet, U-net, HRnet, fusion, segmentation.

## I. INTRODUCTION

Segmenting brain tumors, which means identifying and delineating the boundaries of tumors within brain images, is a critical area of study in medical research. The process is crucial for diagnosing, planning treatment and monitoring the progression of brain tumors. Over the years, this topic has garnered significant attention and effort from researchers, leading to the development of various sophisticated techniques and models.

Advancements in technology and research have led to the creation of several effective models specifically designed to segment brain tumors accurately.These models use various algorithms and approaches, often leveraging machine learning and deep learning techniques, to identify and isolate the regions in medical images where tumors are present.These models are evaluated based on their accuracy , efficiency and ability to generalize across different datasets.The study

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

described in this paper undertakes a comparative analysis of different well known brain tumor segmentation models like HRnet, U-net and ResUnet, specifically focusing on fusion of CT (Computed Tomography) scans and T2-weighted MRI (Magnetic Resonance Imaging) images.CT imaging is crucial for brain tumor diagnosis and management because it provides high-resolution anatomical details, quickly detects calcifications and hemorrhages, and offers excellent bone visualization, all of which are essential for accurate diagnosis, surgical planning and emergency assessments.T2 MRI images are a type of magnetic resonance imaging that provides detailed images of the brain, useful for identifying abnormalities like tumors. Additionally, CT scans complement MRI by providing rapid imaging and specific anatomical information that enhances the overall understanding of the tumor's characteristics and its impact on surrounding brain structures.This paper evaluates how 3 different models, HRnet, U-net and ResUnet perform in segmenting tumors from T2 MRI images.

Additionally, the paper extends the comparison by including a novel approach involving fusion images.Fusion images are created by combining information from different imaging modalities, in this case, CT (Computed Tomography) and T2 MRI images. The fusion method aims to leverage the strengths of both the modalities to enhance the accuracy and reliability of the segmentation process.

In the context of this research, the fusion method [our paper reference] integrates CT images and T2 MRI images into a single composite image. CT image provide excellent anatomical detail and are particularly good at visualizing bone structures, while T2 MRI images offer superior soft tissue contrast, making them effective in highlighting tumors.By combining these two types of images, the fused image potentially provide a richer source of information, which could lead to better segmentation performance compared to using either modality alone.The paper aims to determine whether this fusion approach offers a significant advantage over traditional methods that use single modality images for brain tumor segmentation.

The main objective of this work is to develop a computerized framework for detection brain tumor factors using advanced technologies such as machine learning, as described below:

1. The primary goal is to design and develop a robust and comprehensive segmentation method that integrates multiple imaging modalities, including CT scans and MRI, to accurately segment various types of brain tumors.
2. To enhance early detection of brain tumors by effectively integrating multimodal information. This involves developing a model capable of identifying heterogeneous tumor regions that may be difficult to detect using single modality alone.
3. The study seeks to attain greater accuracy in brain tumor segmentation compared to conventional single modal approaches. By combining data from multiple imaging modalities, the goal is to develop a segmentation model that can more effectively capture variations in tumor appearance, size and location.
4. The study aims to confirm the effectiveness of the proposed multimodal segmentation method using diverse and real world datasets. This includes assessing the model's performance across various tumor types, sizes and imaging conditions to ensure its robustness and adaptability.
5. A key objective is to compare the proposed multimodal approach with traditional single-modal methods, highlighting its superiority in accuracy, sensitivity, specificity and overall segmentation quality through various evaluation metric parameters.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

## II. RELATED WORK

MRI images are renowned for their exceptional quality in the medical field. However, they may occasionally lack certain details that are crucial for accurately identifying or segmenting tumors.Additionally , the transition between tumorous and non-tumorous regions is often very gradual, making it challenging to delineate brain tumors precisely. Furthermore, the presence of water or bleeding in the tumor area can complicate matters, as conventional methods often struggle to distinctly highlight the tumor within the overall abnormal region.

Brain tumor segmentation is a crucial step in the diagnosis and treatment planning of brain tumors. Accurate segmentation can significantly impact the clinical outcome by aiding in precise tumor delineation , monitoring tumor progression, and planning surgical or radiotherapy interventions. This survey aims to provide a comprehensive overview of the methodologies and advancements in brain tumor segmentation, highlighting the strengths and limitations of various approaches.Early methods for brain tumor segmentation primarily relied on traditional image processing techniques. These methods include thresholding, region growing and clustering based approaches. Although straightforward to implement, these methods often struggle with the complexity and variability of tumor experience.

Various machine learning and deep learning techniques have been widely employed for identifying brain tumors. In [2] , researchers utilized the capsule neural network to classify different types of brain cancers using an open database and tested it with the TGCA-GBM dataset from the TCIA. Compared to other systems, this approach shows significant improvements in classification accuracy while requiring less computational effort and reducing both training and prediction times. However, upon evaluating and testing the proposed method, it becomes evident that the capsule neural network-based classifier outperforms convolutional networks.

Brain tumors vary in location , shape, size and contrast, often overlapping with healthy tissue. Hu et al. developed a decision tree classifier using hand-crafted textual features from biopsies to predict tumor molecular alterations [3]. In contrast, deep learning (DL) methods automatically learn and extract relevant features, analyzing patterns at multiple levels - from basic shapes and edges to complex textures and patterns -without needing manual feature selection. Researchers have explored various ML techniques for brain tumor segmentation.Amin et al. developed an automated network using a support vector machine (SVM) with different kernels, showing high efficiency on the Harvard and Rider datasets [4]. Mehmood et al. used a self organizing map (SOM) clustering algorithm, achieving 76% accuracy for brain lesion segmentation[5]. Demirhan and Guler applied SOM and learning vector quantization (LVQ) for white matter (WM) and gray matter (GM) segmentation [6]. Zexuan et al. used generalized rough fuzzy C -means clustering for tumor segmentation [7]. The Adaptive Fuzzy K-mean (AFKM) technique improved upon fuzzy C-means (FCM) offering better qualitative and quantitative results for segmenting WM, cerebrospinal fluid (CSF), and GM[8]. Most research on brain tumor segmentation has focused on machine learning (ML) techniques, which are well suited for handling large datasets. However, some ML methods rely on manually segmented training images, which are costly and labor-intensive, requiring expert radiologists. Consequently, typical ML approaches often need human intervention and feature extraction to distinguish tumor properties in imaging data [9][10]. Havaei et al. used a Convolutional Neural Network (CNN) for brain tumor segmentation, achieving a 0.88 dice score and reduced segmentation time[11]. Pereira et al. also achieved a 0.88

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

dice score with their CNN based system [12]. A 3D CNN model demonstrated a dice score of 0.89 for brain lesion segmentation[13]. An automated deep neural network (DNN) model for MRI scans reported a 0.72 dice score[14]. A fully convolutional residual neural network (FCR-NN) achieved a 0.87 dice score for tumor segmentation[15]. Another DNN based method also attained a 0.87 dice score[16]. Additionally , a Fully Convolutional Network (FCN) provided accurate tumor segmentation using MRI scans (T1, T1c, T2, and Flair)[17].

Despite strong benchmark results, deep learning methods for brain tumor segmentation still face limitations. These methods often struggle with accurately delineating visual objects and maintaining spatial consistency and appearance in the segmentation results.

Mittal M. et al. proposed a combined framework integrating Stationary Wavelet Transform (SWt) with Convolutional Neural Networks (CNN) for brain tumor segmentation to improve model accuracy[18]. Instead of using Fourier Transform, SWT was employed for feature extraction, which is more effective for handling discontinuous data. This was followed by a Random Forest (RF) method for classification., resulting in a 2% accuracy improvement over traditional CNN approaches. Nilesh Bhaskarrao et al. introduced a segmentation framework using Berkeley Wavelet Transform (BWT) combined with Support Vector MAchines (SVM) [19]. BWT was used for feature extraction and SVM was applied for classification, achieving results of 96.51% accuracy, 94.2% specificity and 97.72% sensitivity.Additionally, another study implemented a two-stage framework combining RF and SVM (RF-SVM) for tumor lesion segmentation, where RFwas used to learn tumor labels and SVM classified these labels [20]. Zhao et al. employed a hybrid technique of CNN and Convolutional Random Fields (CRFs) for brain tumor segmentation, achieving a Dice score of 0.87%[21].

Compared to traditional machine learning algorithms, deep learning techniques have proven more effective for segmenting and classifying brain tumor MR images. This study thoroughly examines the significant progress in deep learning approaches from 2010 to 2020. Deep learning networks, with their multiple hidden layers, represent input data through various extraction layers, addressing many challenges faced by conventional machine learning methods. Moreover, these techniques possess self -learning and generalization capabilities, facilitating accurate quantitative analysis of medical imaging features. Consequently, deep learning-based methods achieve precise detection of neurological disorders and are highly regarded in the medical image processing field[22].

In the paper[23], the authors reference CBTRUS statistics estimating that 18,600 individuals will succumb to brain cancer in 2021. Early diagnosis through multimodal imaging can potentially reduce this mortality rate. Manual detection of brain tumors from MRIs and CT scans is not only time-consuming but also prone to human error. Machine learning techniques offer faster and more accurate detection compared to traditional methods.The study employs the Image Fusion technique for preprocessing, simplifying and accelerating feature extraction. This system can serve as a decision-support tool for identifying brain tumors and aid in remote triaging, thereby reducing hospital workload. This research employs the Image Fusion technique for preprocessing, which streamlines and expedites feature extraction. For image segmentation, the U-net architecture is utilized.For classification, U-net, ResNet50 and CNN models are implemented. Among these, ResNet50 achieved the highest accuracy at 98.96%, followed closely by U-net with an accuracy of 97.99%.However , the research is based on a public dataset due to

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

the difficulty of collecting real-time data during the pandemic. Future plans include training the models on real-time data to enhance their clinical applicability. This approach promises to provide substantial clinical support and contribute to lowering brain cancer mortality rates.

## III. PROPOSED METHODOLOGY

The proposed methodology aims to evaluate and compare the performance of three state-of-the-art segmentation models on two types of brain images for tumor segmentation: T2 weighted MRI images and Fusion images made by combining CT and MRI images. By combining important features from both the modalities into a single image helps in highlighting the features present in the image better. For example, CT image can capture bleeding or water accumulation better than MRI, whereas MRI generally captures more details than other modalities. The goal of our research is to demonstrate the superior performance of our fusion technique over traditional T2-weighted MRI Imaging using various recent Deep Neural Networks. The evaluation of these models is conducted using comprehensive metrics such as the Dice coefficient, Hausdorff distance, and conformity Index on multiple real-world data collected from Pathology labs.
Overall, this study contributes to the field of medical imaging by providing a comprehensive framework that not only improves segmentation accuracy but also offers insights into the synergistic benefits of multimodal image fusion.

### A. Data Acquisition:

The Magnetic Resonance - Computed Tomography (MR-CT) Jordan University Hospital (JUH) dataset was utilized for training the segmentation models in this study. The dataset was collected with Institutional Review Board (IRB) approval from the hospital, and informed consent was obtained from all patients. All procedures followed the ethical standards of the World Medical Association's Declaration of Helsinki[24].

The dataset comprises 2D image slices extracted using the RadiAnt DICOM viewer software and transformed into the DICOM image data format with a resolution of 256x256 pixels. It includes a total of 179 2D axial image slices representing 20 patient volumes (90 MR and 89 CT 2D axial image slices). The dataset features MR and CT brain tumor images along with corresponding segmentation masks.

MR images for each patient were acquired using a 5.00mm T Siemens Verio 3T with T2-weighted imaging without a contrast agent, 3 Fat sat pulses (FS), 2500-4000 TR, 20-30 TE, and a 90/180 flip angle. CT images were captured with a Siemens Somatom scanner with a 2.46mGY.cm dose length, 130KV voltage, 113-327 mAs tube current, topogram acquisition protocol, 64 dual source, one projection, and a slice thickness of 7.0mm. Smooth and sharp filters were applied to the CT images. The MR scans have a resolution of 0.7x0.6x5 $mm^3$, and the CT scans have a resolution of 0.6x0.6x7 $mm^3$.

Additionally,a set of 20 MRI and CT images acquired from a local pathology lab were used. The fusion images were created using the aforementioned fusion technique, as detailed in our accompanying paper. The T2 MRI and Fusion images were fused, followed by annotation to train

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

the model on these fusion images. To enhance the training dataset, data augmentation techniques were employed, ensuring more robust model training.

### B. Training Process

- **Data Augmentation:**

In our training process we applied data augmentation techniques with the following parameters: a rotation range of 0.2, width and height shift ranges of 0.05, shear range of 0.05, zoom range of 0.05, and horizontal flipping, with the fill mode set to nearest. These augmentations were applied to the training data before training all the models resulting in approximately 15,000 images for the training set.

After training the models on MRI and CT images along with their masks, we employed transfer learning to further train the models on new fusion images. This allowed the models to learn the features highlighted in the fusion images. The models were trained for an additional 20 epochs with a learning rate of 0.0001to maintain consistent results.

Three models HRNet [25], ResUNet[26], and UNet[27] were used for brain tumor segmentation. Initially , all models were trained on MRI and CT images to learn the basic features of a brain tumor. The Adam Optimizer was used, as it is the preferred optimizer in the respective papers[25][26][27]. The data was split into 70% for training, 20% for validation, and 10% for testing.

- **HRNet:**

The High-Resolution Network (HRNet) is a neural architecture designed to maintain high-resolution representations throughout visual recognition tasks[26]. Unlike conventional architectures that encode images into low-resolution representations before decoding them back to high-resolution, HRNet continuously exchanges information across multiple parallel convolution streams at different resolutions. This design choice makes it particularly well-suited for tasks requiring high spatial precision, such as semantic segmentation, human pose estimation, and object detection.

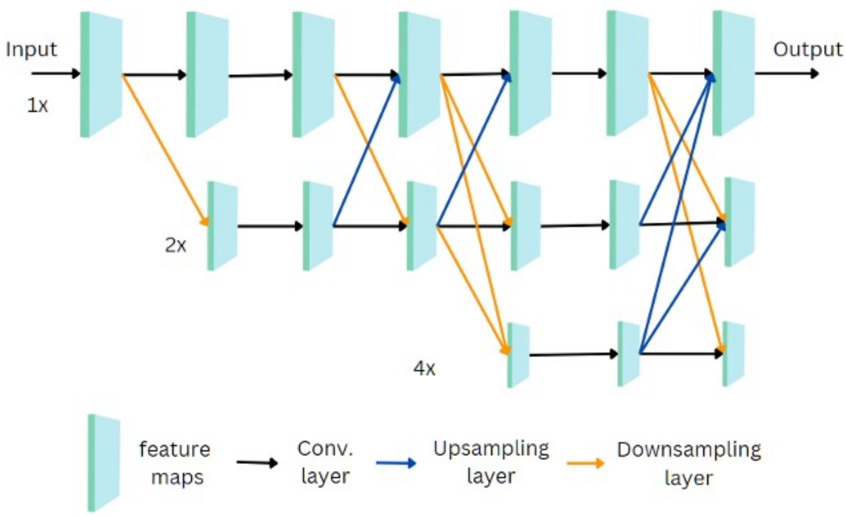


Figure 1: Architecture of High Resolution network

HRNet comprises three primary stages: 1. Parallel Multi-Resolution Convolutions, 2. Repeated Multi-Resolution Fusion, 3. Representation Head, as illustrated in Figure 1. The top layer signifies the Main Convolution layers, while the bottom layers are downsampled layers, with up to four parallel streams that are preserved and fused continuously throughout various stages.[28]

The network initiates with a high-resolution convolution stream. It progressively incorporates lower-resolution streams parallelly as the network deepens,with each new stage introducing an additional lower-resolution layer while retaining the higher-resolution streams from earlier stages.The fusion of lower-resolution layer enriches the data and preserves precise spatial information across different scales.[28]

HRNet's architecture is preferred for segmentation tasks as it maintains the high-resolution spatial information throughout the network. This leads to more precise boundary detections and better overall segmentation performance. The continuous exchange of multi-resolution information ensures that the high-resolution details are preserved, which is crucial for brain tumor segmentation where spatial accuracy is an important parameter.

- **ResUNet:**

ResUNet is an advanced deep learning model that merges components from both Residual Networks (ResNet) [26] and U-net [30], forming a hybrid structure that leverages the advantages of each. Introduced by He et al. in 2015[29], Residual Networks (ResNet) transformed deep learning by mitigating the vanishing gradient issue, which often obstructs the training of very deep networks.ResNet employs residual learning to facilitate the training of significantly deeper networks than those previously used. U-Net, created by Ronneberger et al. in 2015[30], was initially designed for biomedical image segmentation but has since been widely applied in various domains requiring pixel-level classification. The encoder-decoder framework utilized by U-net first reduces and then increases the input dimensions to capture features at multiple scales. U-Net[30] also incorporates skip connections that convey feature maps from the encoder to the corresponding layers in the decoder. These connections ensure the decoder accesses high-resolution features, which are essential for accurate localization and boundary detection.

ResUNet[26] incorporates residual blocks within the encoder, utilizing shortcut connections and identity mappings derived from ResNet. Additionally, ResUNet employs skip-connections between the encoder and decoder to preserve high-resolution information, aiding in precise segmentation boundaries and small structures. Distinct from other convolutional neural networks (CNNs), ResUNet leverages a custom loss function to balance pixel-wise accuracy and boundary precision, resulting in enhanced performance and quicker convergence. This hybrid method produces a robust segmentation model ideal for numerous applications demanding high accuracy and detailed segmentation.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

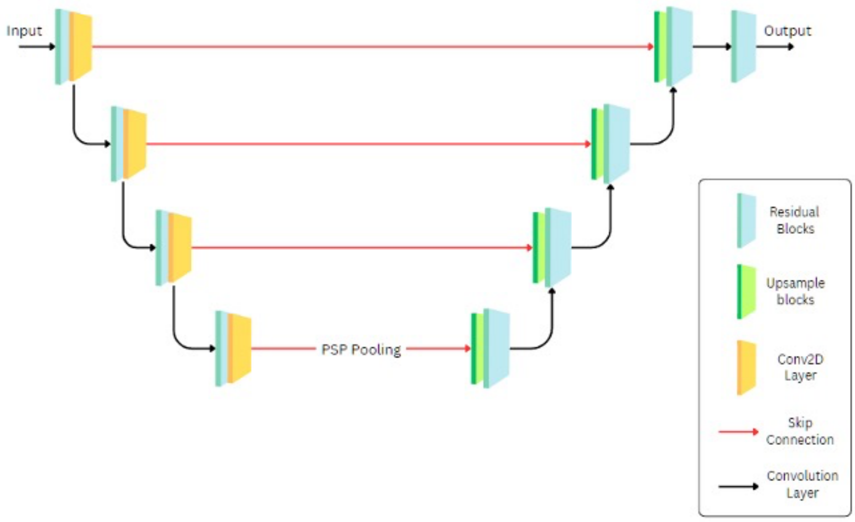



Figure 2: Architecture of ResUNet

The ResBlock in ResUNet is different as compared to UNet, Below Figure shows the residual block that is used in ResUNet, Each unit within the residual block has the same number of filters with all other units. where the different channels designate different dilation rates. Also PSPPooling is used to capture the global contextual information by aggregating features from different subregions of the input at multiple scales.

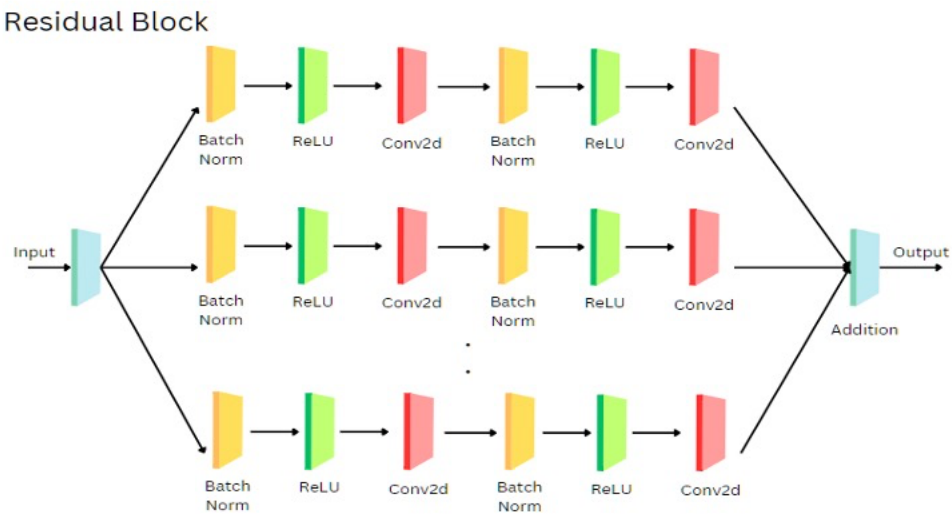



Figure 3: Architecture of Residual Block of ResUNet

ResUNet surpasses traditional models like U-Net and HRNet by integrating residual connections and atrous convolutions, which improve training stability, feature representation, and segmentation accuracy, particularly for tasks requiring precise boundary delineation and multi-scale feature integration.

- **Unet**

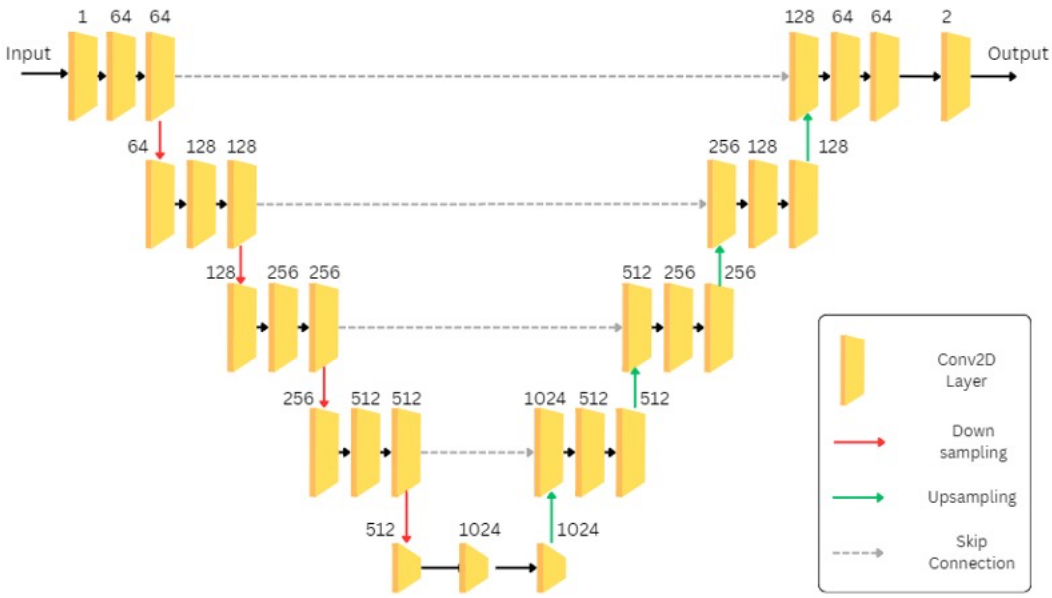
U-Net[27] is a convolution neural network architecture that excels in segmentation tasks. U-Net[27] has gained significant popularity due to its ability to produce high-quality segmentation results with relatively few training images.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

The architecture of U-Net[27] consists of a Encoder (Contracting Path) and a Decoder (Expansive Path). This makes the famous U shaped structure that the Network is named after. U-Net[27] has gained significant popularity due to its ability to produce high-quality segmentation results with relatively few training images.

The U-shaped design allows for precise localization of features while maintaining contextual information. The contracting path follows a typical Neural Network architecture where Convolution layers are present followed by an Activation function (which is ReLU incase of U-Net) and a Softmax layer. The decoder path consists of an upsampling layer followed by a 2x2 convolution that halves the number of features while doubling the size of input. Similarly, the upsampling layer is also followed by a ReLU activation function. In the end a final 1x1 convolution is used to map all components with the desired number of output classes.

The reason why U-Net is preferred for segmentation tasks is due to its ability to capture both localization and context[27]. It also performs very well when we have a limited amount of training data and uses skip connections to preserve finer-grained details. In the particular paper referred above, the model was trained with a learning rate of 0.01 and a batch size of 1, and used weighted cross-entropy loss to enhance the dataset and mitigate overfitting[27]. These hyperparameters were selected to optimize the model's performance on biomedical image segmentation tasks, balancing training time and accuracy.




As shown in figure 4 the Unet architecture resembles a U-shaped architecture that is formed due the use of upsampling and downsampling layers. The layers in the encoder part of the model that have the input shape and number of channels are connected using a skip connection to a layer that has the same input shape and the same number of channels.

- **Transfer Learning**

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

In order to develop an efficient model with a low amount of training data is a very challenging task and in order to achieve optimum results we are using Transfer learning. The models are first trained on the MRI images for 20 epochs with a learning rate of 0.001 so that the model captures information about the tumors better. Once each model is trained on the MRI images the new fusion images are used for training for the same number of epochs. Using augmentation we trained the model with 1100 Fusion images. The learning rate was kept 0.001 for training on Fused imagest too. To keep the analysis fair between different models all the models were trained with the same number of epochs.

At the end of training with MRI and Fusion images the model has better Accuracy of Validation Set of 99.49% for HRNet, 98.10% for ResUNet, and 99.48% for UNet, respectively as compared to directly training the model with Fusion images which results in a lower accuracy.

## IV. RESULTS AND DISCUSSION

To rigorously evaluate and compare the performance of segmentation models on two distinct image datasets, we implemented a comprehensive analysis using a variety of performance metrics. This analysis was conducted on a curated set of 10 images from each dataset. By averaging the results across all images, we aimed to present a clear and objective assessment of each model's overall efficacy across different types of data.

The evaluation involved the following key metrics:

- Intersection over Union (IoU); This metric was used to quantify the area of overlap between the predicted segmentation and the ground truth relative to the total area covered by both. IoU provides a robust indication of the model's ability to correctly identify the region of interest within the image, offering an overall performance score.
- Dice Coefficient: To further assess the accuracy of the segmentation, the Dice Coefficient was employed. The metric calculates the degree of overlap between the predicted and actual segmentation masks, effectively measuring how closely the model's output aligns with the ground truth.
- Hausdorff Distance: This metric was utilized to evaluate the spatial similarity between the predicted segmentation boundary and the actual boundary. By measuring the maximum distance from a point on the predicted contour to the closest point on the ground truth contour, the Hausdorff Distance provided insights into the precision and reliability of the model's boundary predictions.
- Conformity Index: Recognizing the importance of balancing precision and recall, the Conformity Index was used to evaluate the trade-off between false positives and false negatives. The metric is particularly valuable for understanding the model's performance in scenarios where over-or under segmentation can significantly impact the outcome.

These metrics were carefully selected to endure a comprehensive evaluation of segmentation accuracy, robustness and reliability across diverse image types. By applying these measures, we aimed to provide a thorough comparison of model performance, highlighting strengths and areas for improvement in different segmentation scenarios.

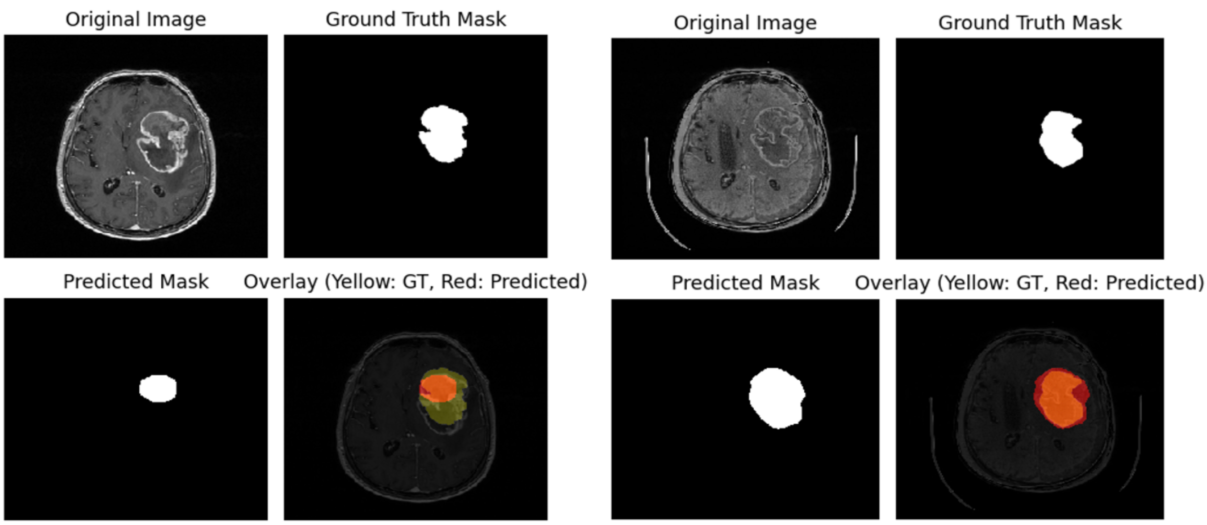
To create a Test set which can be used for benchmark, we took help of a local pathology lab to collect data of several patients. 6 unique cases were selected from the total data as a sample. A

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

T2 MRI slice and a CT slice was taken for each case, which further were used to generate a Fusion image. All the models were tested with this data to evaluate the performance of these models.

**1. HRNet:**

HrNet shows the best results out of all the algorithms. Figure 5 (a) shows the segmentation results done on MRI image, the predicted tumor region is lesser than ground truth. whereas in the fusion image the predicted mask closely resembles the ground truth with some minor error.

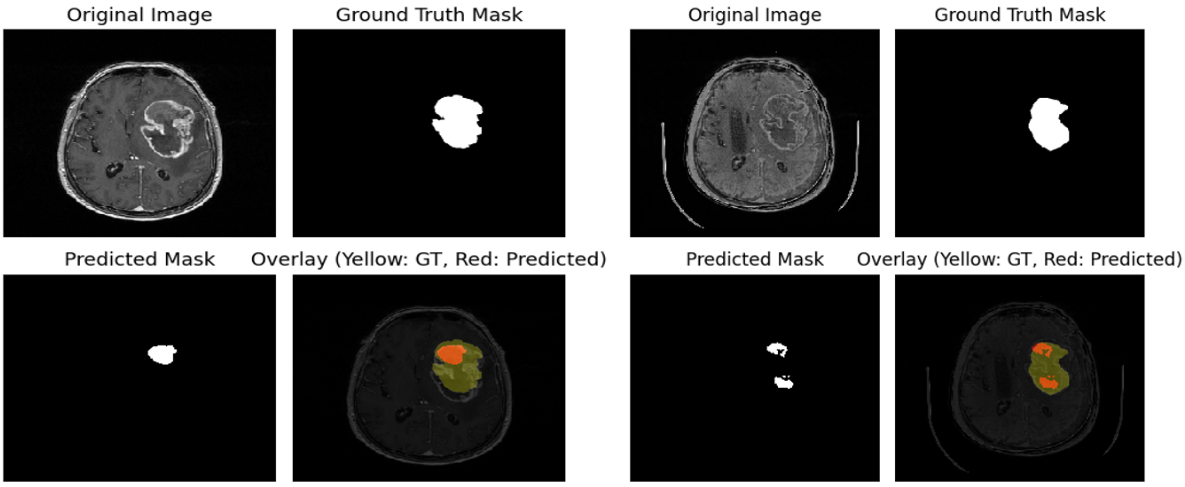



**(a)** **(b)**

The IOU score on the compiled test was 0.278 while the average IOU score for Fusion images was 0.5231 which is an increase of around 88.10%. Similarly, the Dice Metric increased from 0.0022 for MRI to 0.0040 with Fusion, reflecting better overlap between predicted and true segmentation. The Hausdorff Distance (HD), which measures the maximum segmentation error, decreased from 57.9268 for MRI to 32.4998 with Fusion, indicating more accurate boundary delineation. Additionally, the Conformity Index (CI) improved from 0.2781 with MRI to 0.5231 with Fusion.

**2. ResUNet:**

The performance of ResUNet is subpar as compared to other model, as show in Figure 6 (a) the Predicted mask covers only a small part of the ground truth mask just like the one we got using HRNet. However, the Fusion image does not detects the tumor into two small segments instead of one.




**(a)** **(b)**

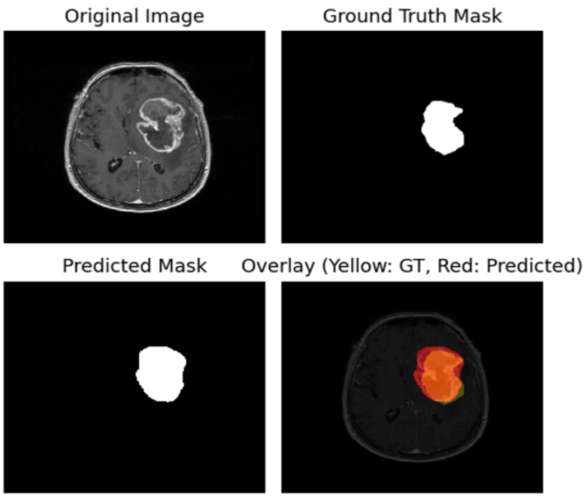
Looking at the results from testing ResUNet with the benchmark dataset we can say that the ResUNet is well trained on the MRI images that were used earlier in the training process. However, while training the model on Fusion images using Transfer learning the model as not able to accurately capture and train according to Fused Images. The Intersection Over Union (IoU) score for MRI images is 0.5292, significantly outperforming the Fused Images score of 0.1506, indicating a superior overlap between the predicted and actual segmentation for MRI images. The Dice Metric also shows a better result for MRI at 0.0049, compared to 0.0015 for Fused Images Additionally, the Hausdorff Distance (HD), which measures the maximum deviation in boundary segmentation, is lower for MRI at 22.9645 compared to 28.8188 for Fused Images, reflecting average boundary precision for both models with MRI being better.. Moreover, the Conformity Index (CI) for MRI is 0.0020, which is higher than the score of 0.0008 for Fused Images.

**3. UNet:**

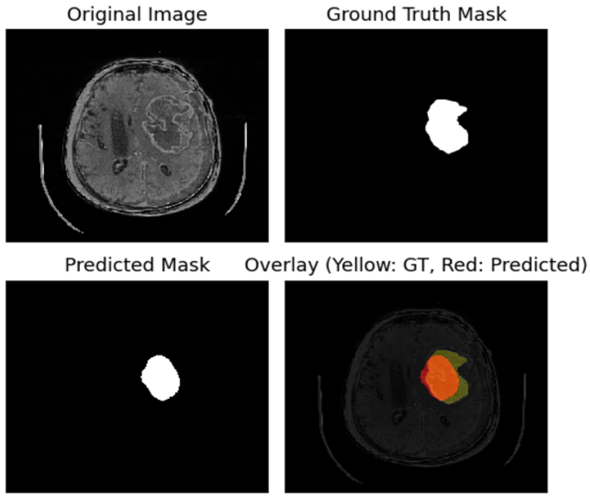
The Unet based model performs better than ResUNet model in this case. as shown in Figure 7 (a) the model detects the tumorous region however it predicts the tumorous region being bigger than the ground truth, this is a repeating pattern observed is many test cases leading to False Positives. Since the UNet shows good performance having a high number of False Positive makes the algorithm less viable as compared to other algorithms

The Intersection over Union (IoU) score for Fusion is 0.4939, which is an improvement over the MRI score of 0.3440, indicating a better alignment between the predicted and actual segmentation regions. The Dice Metric remains consistent at 0.0057 for both methods, but the Hausdorff Distance (HD), which measures the boundary segmentation error, is reduced from 63.8113 with MRI to 50.4116 with Fusion, reflecting enhanced boundary accuracy. Additionally, the Conformity Index (CI) improves from 0.3440 with MRI to 0.4939 with Fusion, demonstrating more consistent and accurate segmentation results with the Fusion approach..

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)




(a)




(b)

We have compiled Table 1 with all the values from the test with the Average of Scores for MRI and Fusion Images for all the models mentioned above. The Values are average of 6 unique cases. UNet performs well in both MRI and Fusion images maintaining good performance, however it fall slightly behind when considering the False Positive issue that was observed. ResUnet performs very well with MRI images however the model fails to adequately capture the Features of Fused images which resulted in poor performance as compared to other models. HRNet strikes a good overall score with Fusion images specifically excelling in IoU and Conformity Index (CI).

**Metric Parameter**

| Metric Parameter | HRNet | | ResUNet | | UNet | |
|---|---|---|---|---|---|---|
| | MRI Images | Fusion Images | MRI Images | Fusion Images | MRI Images | Fusion Images |
| IoU | 0.2781 | 0.5231 | 0.5292 | 0.1506 | 0.3440 | 0.4939 |
| Dice Metric | 0.0022 | 0.0040 | 0.0049 | 0.0015 | 0.0057 | 0.0057 |
| Hausdorff Distance (HD) | 57.9268 | 32.4998 | 22.9645 | 28.8188 | 63.8113 | 50.4116 |
| Conformity Index (CI) | 0.2781 | 0.5231 | 0.0020 | 0.0008 | 0.3440 | 0.4939 |

## V. CONCLUSION AND FUTURE SCOPE

In summary, this methodology outlines a comprehensive approach to evaluating the performance of three segmentation models on T2-weighted MRI and fusion images. Based on the above results we concluded that HRNet is more preferable than the other options due to its performance across different real-world test cases. Moreover, it also scores a higher accuracy of 99.49%, which is

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 20 No. 01 (2026)

higher than other models. When compared with the MRI counterparts for each model, the performance is vastly better than other models in most of the test metrics. On an average there is a 10-15% increase in performance of these models across different test metrics. By rigorously comparing these models, we aim to demonstrate the effectiveness of our fusion technique in improving tumor segmentation accuracy, ultimately contributing to better diagnostic and treatment planning in clinical practice. However, the tests shown here are done with a small amount of data due to the inability to use more data. In Future, we can expand upon this research by testing the Fusion technique with more data and with other Deep Neural Networks to further improve the performance.

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