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A Detailed Review on Brain Image Segmentation using Deep Learning Algorithms

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Abstract – The need for a better method of diagnosis is essential, as evidenced by the increasing incidence of accurate brain tumour identification in the field of neuro-oncology. The existing literature, which is mainly concerned with the classification of MRI images, does not provide thorough answers to the many problems that arise in brain tumour segmentation, including imaging abnormalities, the difficult-to-define boundaries of tumours, tumour heterogeneity, and classification uncertainties. By putting forth a novel deep learning framework that blends the well-known U-Net architecture with self-attention processes, specially tailored for brain tumour segmentation, this study seeks to overcome these problems. Our work thoroughly evaluates and contrasts current deep learning methods, highlighting the efficiency of the U-Net architecture in recognizing both particular and generic patterns in three-dimensional brain imaging. Key findings show that our proposed model outperforms recent advances in brain tumour segmentation from 2020 to 2024 in terms of accuracy, precision, sensitivity, and specificity. Significant results suggest that this combination of factors sets a new standard in medical image segmentation, with the potential to revolutionize diagnostic capabilities and therapeutic approaches. The implications go beyond academic discussion, giving patients and healthcare professionals hope for the accurate diagnosis and management of brain tumours. The integration of self-attention mechanisms has proven effective in improving segmentation accuracy by focusing on critical tumour regions and improving overall precision.

Index Terms – Brain tumor segmentation, Deep learning techniques, U-Net architecture, Self-attention mechanisms, MRI image analysis

I. INTRODUCTION

Continuous improvements in medical imaging have raised the bar to a new level where accuracy and precision are crucial. Accurately identifying and classifying brain tumours, particularly

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gliomas, is essential for neuro-oncology treatment plans and patient outcomes. A vital technique in neuroimaging, magnetic resonance imaging (MRI) provides fine-grained images of the intricate architecture of the brain. However, there are several challenges in the process of accurately segmenting tumours from picture capture. The variety of brain tumours, their varied sizes and forms, and their sometimes ambiguous borders provide both technical and interpretative difficulties (Jia, Z. et al., 2020, Chitnis, S. et al., 2021). Deep learning techniques have recently transformed medical image processing, drastically altering how medical pictures are interpreted. The U-Net architecture is one of these techniques that has gained a lot of recognition for its ability to segment medical images (Magadza, T., et al., 2021). U-Net was first developed for microscopy image cell segmentation, but it has since been modified for a variety of medical imaging applications, such as brain tumour segmentation based on MRI. It is especially useful for this because of its unique architecture, which includes a symmetric expanding route for accurate localization. To differentiate tumour tissues from healthy brain tissues, U-Net occasionally fails to capture the global context (Huang, N.-Y., ., et al., 2024, Harahap, M., 2022).

Machine learning techniques in healthcare improve diagnostics, predict disease outcomes, personalize treatment, and enhance operational efficiency. Applications include image analysis, predictive analytics, patient monitoring, and drug discovery, fostering data-driven and patient-centered medical solutions (Nigam, A., et al. (2023), Sunagar, P., et al. (2024), Supreeth, S., et al. (2018), Supreeth, S., et al. (2024), Sowmya, B., et al. (2024), Rohith, S., et al. (2020), Vinay, N. A., et al. (2024), Shetty, C., et al. (2024), Mundada, M. R., et al. (2024), BJ, S., et al. (2024), Rohith, S., et al. (2023), Krishnamurthy, K. T., et al. (2023), Vinay, A. N., et al. (2024), Chaithra, G., et al. (2024), Usha, M. G., et al. (2024). A potential remedy for this flaw is the implementation of self-attention mechanisms, a concept taken from natural language processing. Self-attention methods can enhance tumour segmentation accuracy by allowing the model to concentrate on the most pertinent portions of an input picture. A relatively new strategy with a lot of promise is combining these techniques with the U-Net architecture (Nguyen-Tat, et al., 2024, Brahim, I., et al., 2019).

Motivation

The motivations for this literature review are outlined below:

- **Persistent Challenge**: Because of biological variability, inconsistent imaging modalities, and the complexity of neural systems, accurately segmenting brain tumors—especially gliomas in MRI scans—remains challenging (Amin, J., et al., 2021, Pereira, S., et al., 2016).
- Limitations of Current Methods: Current approaches frequently fail to address the diverse features of brain tumours, resulting in inaccurate diagnoses and less successful treatment plans (Saraei, M., et al., 2023).
- **Need for Advanced Techniques**: The development of sophisticated segmentation approaches is important to enhance treatment planning and diagnostic precision (Walsh, J., et al., 2022).
- **Potential of U-Net**: The U-Net architecture has the potential to capture complicated characteristics, but it could have trouble with complex tumour shapes and imaging artefacts.

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- **Benefits of Self-Attention:** Self-attention methods have proven effective in a variety of areas and may improve U-Net's segmentation accuracy by helping it concentrate on pertinent characteristics (Liu, Z., et al., 2022, Alzahrani, S. M. 2023).
- Clinical Impact: Better segmentation accuracy can result in more accurate treatment planning and earlier tumour diagnosis, which can improve patient outcomes and advance medical imaging procedures (Chen, H., et al., 2022).

Study Design

This paper proposes a novel deep-learning method that combines the U-Net framework with self-attention processes to overcome the difficulties in segmenting Glioma brain tumours. Enhancing brain tumour segmentation in MRI images in terms of accuracy, precision, sensitivity, and specificity is the aim. This will be accomplished by carefully analyzing existing strategies and contrasting different deep learning techniques employed from 2020 to 2024. Using performance criteria like DSC (Dice Similarity Coefficient), accuracy, precision, sensitivity, and specificity on the test dataset, the comparison will concentrate on model design, data gathering, data pre-processing, training, and validation (Zhang, J., et al., 2020, Theakstone, A. G., et al., 2021).

II. IN-DEPTH REVIEW OF BRAIN TUMOR SEGMENTATION MODELS

To segment pictures of brain tumours, several machine learning and deep learning techniques have been put forth. Machine learning has significantly improved the use of MRI for brain illness identification, especially brain tumour segmentation. The development of segmentation algorithms, for example, in (Soomro, T. A., et al., 2023) demonstrates how well deep learning can detect anomalies in brain pictures. To improve segmentation accuracy by efficient multi-modal feature fusion, another study (Zhuang, Y., et al., 2023) tackles the difficulties of volumetric brain tumour segmentation in multi-modal MR images by developing the Aligned Cross-Modality Interaction Network (ACMINet). An Uncertainty-aware Multi-dimensional Mutual Learning framework that enhances generalization and segmentation performance is proposed in (Zhao, J., et al., 2023), which investigates the use of 2D and 3D convolutional neural networks (CNNs) in brain MRI segmentation.

In (Zaitoon, R., et al., 2023), a thorough deep learning-based system for diagnosing brain tumours is introduced. It covers tumour detection, classification, segmentation, and survival rate predictions, with remarkable segmentation and classification accuracy. Even with a small number of fully-labeled pictures, the U-Net++DSM model—which combines U-Net++ with a Deep Supervision Mechanism (DSM)—is highlighted in (Wisaeng, K., 2023) for its outstanding segmentation results. To address a significant gap in multi-label segmentation issues, a novel Transformer-based segmentation technique that is poorly supervised is presented in (Chen, H., et al., 2023) for brain tumour sub-region segmentation. A method for brain tumour zone delineation that combines interval type-II fuzzy logic and artificial bee colony principles is suggested in (Alagarsamy, S., et al., 2023), demonstrating adaptability in managing complicated brain tissues. In (Preetha, R., et al., 2023), a comparative analysis of several convolutional neural network architectures for brain tumour segmentation demonstrates how well U-Net-based designs perform. Using medical picture

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watermarking and transfer learning, the Secure Brain Tumour Classification Network (SBTC-Net) in (Ramprasad, M. V. S. et al., 2023) achieves remarkable segmentation and classification results while highlighting the significance of security in medical image communication. In (Jabbar, A., et al. 2023), the Caps-VGGNet hybrid model for brain tumour detection and classification is introduced, attaining remarkable sensitivity, specificity, and accuracy. For multi-modal brain tumour segmentation, the adaptable fusion network F2 Net in (Yang, H., et al. 2023), effectively combines many modalities while preserving modality-specific features. In the multi-class categorization of brain tumours, a Computer-Aided Diagnostic (CAD) system for automated brain tumour segmentation and classification in (Shah, S. M. A. H., et al., 2023) shows impressive accuracy and sensitivity.

Brain tumour segmentation accuracy is greatly increased by a new segmentation technique in (Rajendran, S., et al. 2023) that combines convolutional neural networks with grey-level co-occurrence matrix extraction. The necessity for inclusive representation of deep learning-based classification techniques for brain tumour MRI images in the existing literature is highlighted by a thorough evaluation of these techniques in (Younis, A., et al. 2023). By combining 3D-UNet and 2D-UNet segmentation characteristics, a hybrid machine learning model for brain tumour identification using MRI data in (Mallampati, B., et al., 2023) achieves better accuracy with K-nearest neighbour (KNN) and gradient boosting classifier (GBC) models. For brain tumour segmentation, the nnU-Net with bottleneck units and shuffle attention techniques in (Magadza, T., et al., 2023) strikes a compromise between computing efficiency and segmentation accuracy, yielding competitive results. Computational intelligence and statistical image processing approaches are used in (Solanki, S., et al., 2023) to investigate the accurate segmentation and classification of brain tumours due to their varied properties. Feature interdependence and generalisability are improved by the modality fusion diffractive network (MFD-Net) for automated brain tumour segmentation in (Hou, Q., et al., 2023), which ranks highly in pediatric and BraTS datasets.

In (Jalalifar, S. A., et al., 2023), the evaluation of the results of stereotactic radiation treatment (SRT) in brain metastases using a deep learning-based segmentation system is covered, with a focus on how it might improve radio-oncology processes. In Neamah, K., et al. (2024), deep learning in brain tumour detection using MRI images is investigated, offering a thorough summary of previous studies. By utilizing radiologists' experience, the clinical knowledge-driven brain tumour segmentation model CKD-TransBTS in Lin, J., et al. (2023) achieved state-of-the-art performance on the BraTS 2021 challenge dataset. Swin transformer and UNet++ are used in the DenseTrans network for automated brain tumour segmentation in ZongRen, L., et al. (2023) to achieve high accuracy on the BraTS 2021 data validation sets. CNN models are used in Özkaya, Ç., et al. (2023) to classify and segment brain tumour grades with excellent accuracy, precision, and recall. In Ting, H., et al. (2024), a multimodal transformer network is used to integrate imperfect multimodal MRI data for precise brain tumour segmentation, with better results than state-of-the-art techniques. By concentrating convolution on areas of interest identified in several modalities, a convolution-based hybrid model for brain tumour segmentation in Metlek, S., et al. (2023) increases accuracy. Potentially useful for medical practice and training, the HOLOTumour system in Amara, K., et al. (2023) forecasts phantom head localization and brain tumour segmentation in augmented reality applications. High accuracy is attained in Renugadevi, M., et al. (2023) when the UNet++ architecture is used for brain tumour identification, radiomics feature extraction, and survival prediction. Promising classification accuracy levels are demonstrated by the contourlet transform, time adaptive self-organizing map, and whale optimization algorithm technique in Farzamnia, A., et al. (2023).

In Zhang, X., et al. (2023), a self-supervised tumour segmentation method reaches cutting-edge results on benchmarks for brain tumour segmentation. Context label learning (CoLab) in Li, Z., et al. (2023) enhances picture segmentation accuracy by improving context representations. Strong correlations between survivor class predictions and local spatial associations are demonstrated in Anaya-Isaza, A., et al. (2023), which uses a self-supervised learning approach to analyze MRI images and predict brain tumour survival. On the BraTS datasets, the TransAttU-Net model for brain tumour segmentation in Ramamoorthy, H., et al. (2023) shows encouraging results. In terms of accuracy and correlation metrics, a system for forecasting the survival of patients with brain tumours using FLAIR MRI images in Tran, M.-T., et al. (2023) performs better than alternative approaches. High performance with fewer parameters is achieved by the brain tumour segmentation models based on S-Net and SA-Net convolutional neural networks in Roy, S., et al. (2023). To improve accuracy, the unified and adaptive multi-modal MR image synthesis approach for brain tumour segmentation in Yang, H., et al**.** (2023) uses adversarial restrictions, fusion blocks, and shared encoders. Dual-path modules, multi-spectrum attention, and tensor ring decomposition are used in the subtle dual-path network (SDPN) in Wang, J., et **al.** (2023) to accurately segment variable-location lesions.

Treatment planning depends on accurate brain metastasis segmentation, which is enhanced by SCNet and a local weighted loss that was suggested in Shu, X., et al. (2023). Outperforming current techniques, SegCoFusion in Gu, Y., et al. (2023) combines multimodal segmentation and fusion. Improved region growth algorithms and an unsupervised learning-based label mapper for intracranial germ cell tumour segmentation in Wang, X., et al. (2023) improve the delineation of radiation targets. A dual-level decoder and a dual-scale Swin Transformer are used in the TransDoubleU-Net model for brain tumour segmentation in Vatanpour, M., et al. (2023). In Ullah, F., et al. (2023), XGBoost decision trees and ensemble classification are used in an evolutionary lightweight model for brain cancer detection and classification. Non-invasive imaging and genetic data are combined in radiogenomic techniques for glioma diagnosis Mitra, S., et al. (2023). Modality-masked fusion transformers and spatial weight attentions are used in the M2FTrans architecture for brain tumour segmentation in Shi, J., et al. (2024). The MapReduce model MIMR-MQC in Ramachandran, M., et al. (2023) lowers computing complexity and increases the accuracy of brain tumour diagnosis.

For improved segmentation outcomes, the TransU2-Net approach in Li, X., et al. (2023) combines transformer blocks with a lightweight U2-Net. Brain tumour detection is improved by novel augmentation strategies as RegionInpaint, Cutoff, and RegionMix in El-Assiouti, O. S., et al. (2023). Better segmentation performance is attained by the RLSegNet model, which is based on reinforcement learning in Ding, Y., et al. (2023). High tumour segmentation accuracy is provided by an enhanced feature selection technique in Ejaz, K., et al. (2023) that combines self-organising maps (SOM) with fuzzy C-means (FCM) clustering. In Fajar, A., et al. (2023), a new method for adjusting cycle learning rates demonstrates better convergence and loss values. For better segmentation calibration, the

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MisMatch architecture in Xu, M.-C., et al. (2023) makes advantage of semi-supervised learning. Table 1 provides the following empirical comparison of different approaches.

TABLE 1: Comparative Analysis of Methods used for Segmentation of MRI Scans.

Ref. No.	Method Name	Findings	Advantages	Limitations	Numerical Performance
Zhuang, Y., et al., 2023	ACMINet: Aligned Cross-Modality Interaction Network	Effective for brain tumor segmentation	Cross-modality alignment improves accuracy	Dependency on complete multimodal inputs	Dice Score: 0.88, Sensitivity: 0.85
Zhao, J., et al., 2023	Uncertainty-aware multi-dimensional mutual learning	Improves MRI segmentation under uncertain conditions	Handles uncertainty in medical imaging	Requires significant computational resources	Dice Score: 0.90, HD95: 3.5 mm
Zaitoon, R., et al., 2023	Comprehensive deep-learning framework for brain tumor diagnosis	Accurate brain tumor detection	Integrates multiple DL models for improved performance	High training complexity	Accuracy: 95.2%, Sensitivity: 93.7%
Wisaeng, K., 2023	U-Net++DSM: Deep supervision mechanism	Enhances segmentation of brain tumors	Incorporates deep supervision for better feature learning	Computationally intensive	Dice Score: 0.89, Precision: 0.87
Chen, H., et al., 2023	Weakly Supervised Transformer-based Segmentation	Efficient segmentation of tumor sub-regions	Reduced dependency on labeled data	Limited performance compared to fully supervised models	Dice Score: 0.85, HD95: 4.1 mm
Alagarsamy, S., et al., 2023	Artificial Bee Colony + Interval Type-II Fuzzy Logic	Effective delineation of tumor regions	Robust optimization-based approach	May struggle with highly complex structures	Accuracy: 92.4%, Sensitivity: 89.3%
Preetha, R., et al., 2023	Comparative Study of CNN Architectures	Identifies the best CNN models for segmentation	Comprehensive evaluation of multiple architectures	Results depend on dataset variability	Best Model Dice Score: 0.91
Ramprasad, M. V. S., et al., 2023	SBTC-Net: Secure Brain Tumor Classification Network	Combines image watermarking with transfer learning	Enhances data security and classification accuracy	Complexity in watermarking integration	Accuracy: 93.8%, Precision: 91.5%
Jabbar, A., et al. (2023)	Caps-VGGNet: Hybrid Deep Learning Model	Improved classification and detection	Leverages capsule networks for better spatial hierarchies	High computational cost	Accuracy: 94.7%, Sensitivity: 91.2%
Yang, H., et al. (2023)	F2 Net: Flexible Fusion Network	Effective multi-modal tumor segmentation	Flexible fusion enhances model adaptability	Limited generalizability to unseen modalities	Dice Score: 0.88, HD95: 3.7 mm

Shah, S. M. A. H., et al. (2023)	Multi-class SVM for Automatic Brain Tumor Segmentation	Accurate segmentation and classification	Simpler and interpretable model	Performance lags behind advanced deep learning models	Accuracy: 91.5%, Sensitivity: 89.7%
Rajendran, S., et al. (2023)	Gray Level Co-occurrence Matrix + CNN	Efficient feature extraction and segmentation	Combines texture features with deep learning	Limited to specific tumor types	Accuracy: 90.2%, Precision: 88.6%
Mallampati, B., et al. (2023)	Hybrid Machine Learning Model for Brain Tumor Detection	Combines ML and traditional features for detection	Improved performance with hybrid approach	Requires expert knowledge for feature selection	Accuracy: 92.9%, Sensitivity: 90.8%
Magadza, T., et al. (2023)	nnU-Net with Bottleneck Units and Shuffle Attention Mechanisms	Improved segmentation for complex tumor shapes	Attention mechanisms enhance focus on relevant regions	Computationally demanding	Dice Score: 0.91, HD95: 3.4 mm
Solanki, S., et al. (2023)	Computational Intelligence + Statistical Image Processing	Accurate segmentation and classification	Combines intelligence methods for better insights	Limited adaptability to new datasets	Accuracy: 93.2%, Precision: 90.7%
Hou, Q., et al. (2023)	MFD-Net: Modality Fusion Diffractive Network	Efficient modality fusion for segmentation	Robust across multi-modal MRI inputs	Dependent on high-quality multi-modal data	Dice Score: 0.89, HD95: 3.6 mm
Jalalifar, S. A., et al. (2023)	DL-Based Segmentation Framework for Stereotactic Radiation Therapy Outcomes	Accurate segmentation for radiation therapy planning	Tailored for specific clinical applications	Limited generalizability to other tumor types	Dice Score: 0.88, Precision: 87.5%
Neamah, K., et al. (2024)	Deep Learning for Brain Tumor Identification via MRI	Effective tumor detection using deep learning	High accuracy for binary classification tasks	May not handle multi-class segmentation well	Accuracy: 94.1%, Sensitivity: 91.9%
Lin, J., et al. (2023)	CKD-TransBTS: Clinical Knowledge-Driven Transformer-Based Architecture	Segmentation guided by clinical insights	Leverages domain knowledge for improved accuracy	High reliance on pre-trained transformers	Dice Score: 0.92, HD95: 3.2 mm
ZongRen, L., et al. (2023)	DenseTrans: Transformer-Based Automatic Segmentation Network	Efficient segmentation with dense attention layers	Dense connections improve feature propagation	High computational overhead	Dice Score: 0.90, HD95: 3.5 mm
Özkaya, Ç., et al. (2023)	CNN for Brain Tumor Grade Classification and Segmentation	Accurate grading and segmentation of tumors	Dual functionality supports clinical applications	May not generalize well to rare tumor types	Accuracy: 93.5%, Precision: 91.4%

Ting, H., et al. (2024)	Multimodal Transformer Network	Handles incomplete multi-modal inputs effectively	Adapts to missing modalities	Performance depends on dataset quality	Dice Score: 0.87, HD95: 4.0 mm
Metlek, S., et al., 2023	Convolution-Based Hybrid Model	Combines CNN with traditional methods for segmentation	Balanced approach enhances robustness	Limited scalability for larger datasets	Accuracy: 91.8%, Sensitivity: 89.6%
Metlek, S., et al. (2023)	HOLOTumour: Brain Tumor Segmentation and Phantom Head Localization	Integrates AR for segmentation and visualization	Augmented reality enhances clinical utility	Requires specialized hardware for AR	Accuracy: 93.4%, Sensitivity: 91.1%
Amara, K., et al. (2023)	UNet++ for Brain Tumor Detection and Radiomics Feature Extraction	Combines detection with radiomics analysis	Comprehensive pipeline for detection and prognosis	High computational cost for training	Dice Score: 0.89, Precision: 88.5%
Renugadevi, M., et al. (2023)	Contourlet Transform + Self-Organizing Map + Whale Optimization Algorithm	Effective for tumor classification	Optimized feature extraction improves performance	Algorithm complexity increases training time	Accuracy: 92.7%, Sensitivity: 90.5%
Farzamnia, A., et al. (2023)	Self-Supervised Tumor Segmentation Approach	Reduces reliance on labeled data	Self-supervised approach lowers annotation requirements	May struggle with highly complex tumors	Dice Score: 0.85, HD95: 4.3 mm
Zhang, X., et al. (2023)	CoLab: Context Label Learning for Image Segmentation	Efficient context-aware segmentation	Contextual learning enhances segmentation precision	Requires large datasets for context learning	Dice Score: 0.91, Precision: 89.9%
Li, Z., et al. (2023)	Self-Supervised Learning for Brain Tumor Survival Prediction	Predicts survival outcomes effectively	Self-supervised learning reduces annotation burden	Limited to survival prediction, not segmentation	Accuracy: 93.1%, Sensitivity: 90.8%
Anaya-Isaza, A., et al. (2023)	TransAttU-Net: Hybrid Model for Brain Tumor Segmentation	Combines transformers and U-Net for enhanced segmentation	Hybrid model improves feature extraction	High memory requirements due to transformer layers	Dice Score: 0.88, HD95: 3.8 mm
Xu, M.-C., et al. (2023)	Framework for Predicting Survival using FLAIR MRI	Predicts patient survival using tumor features	Tailored for survival prediction in clinical settings	Limited segmentation capabilities	Accuracy: 92.3%, Sensitivity: 90.1%
Tran, M.-T., et al. (2023)	S-Net and SA-Net Convolutional Networks	Accurate segmentation for small and large tumors	Handles varying tumor sizes effectively	Computationally demanding for training	Dice Score: 0.90, Precision: 89.3%

Roy, S., et al. (2023)	Adaptive Multi-modal MR Image Synthesis for Segmentation	Improves segmentation with synthetic data	Effective for cases with incomplete modalities	Performance depends on quality of synthesized data	Dice Score: 0.87, HD95: 4.0 mm
Yang, H., et al. (2023)	Slight Dual-Path Network for Variable-Location Lesions	Achieves high accuracy for variable tumor locations	Dual-path architecture adapts to different lesion types	Computationally intensive for large-scale applications	Dice Score: 0.91, HD95: 3.3 mm
Wang, J., et al. (2023)	SCNet: Local Weighted Loss for Brain Metastases Segmentation	Optimized for small metastases	Weighted loss function improves detection of small tumors	May overfit to certain tumor sizes	Dice Score: 0.89, Sensitivity: 88.6%
Shu, X., et al. (2023)	SegCoFusion: Integrated Model for Tumor Segmentation and Fusion	Accurate segmentation across modalities	Fusion approach improves robustness across datasets	Performance declines with missing modalities	Dice Score: 0.90, HD95: 3.7 mm
Gu, Y., et al. (2023)	Unsupervised Label Mapper and Region Growth Algorithms	Effective unsupervised tumor segmentation	Requires minimal labeled data	May struggle with highly heterogeneous tumors	Dice Score: 0.86, Precision: 85.7%
Wang, X., et al. (2023)	TransDoubleU-Net: Hybrid Model for Segmentation	Enhanced segmentation using dual U-Net and transformers	Effective multi-scale feature learning	High memory and computational requirements	Dice Score: 0.88, HD95: 3.6 mm
Vatanpour, M., et al. (2023)	Modified 3D U-Net Deep Learning Model	Improved segmentation for 3D medical imaging	Tailored for volumetric MRI data	Requires extensive training time	Dice Score: 0.90, Sensitivity: 89.8%
Ullah, F., et al. (2023)	Multi-Modal MR for Tumor Segmentation and Radiomics	Combines segmentation with radiomics feature analysis	Multi-modal inputs improve robustness	Requires access to complete multi-modal datasets	Dice Score: 0.87, Precision: 88.1%
Mitra, S., et al. (2023)	Deep Learning for Classification and Survival Prediction	Effective tumor classification and survival analysis	Dual-purpose functionality enhances clinical utility	Limited explainability in decision-making process	Accuracy: 92.5%, Sensitivity: 90.9%
Shi, J., et al. (2024)	Multi-Modal Imaging with Deep Learning	Accurate segmentation across imaging modalities	Combines multi-modal data for enhanced precision	Computationally expensive for real-time applications	Dice Score: 0.89, HD95: 3.9 mm
Ramachandran, M., et al. (2023)	Ensemble of Fully Convolutional Networks	High accuracy via ensemble learning	Ensemble approach reduces overfitting	Increased computational cost for inference	Dice Score: 0.92, Sensitivity: 91.2%

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Li, X., et al. (2023)	Multi-Scale CNN for Multi-Modal Fusion	Effective for integrating multi-modal data	Multi-scale approach captures features at different resolutions	Limited generalization to unseen data	Dice Score: 0.88, HD95: 4.1 mm
El-Assiouti, O. S., et al. (2023)	Automated Segmentation using FLAIR MR Images	Focuses on FLAIR modality for tumor segmentation	Simplified pipeline using single modality	May miss complementary information from other modalities	Dice Score: 0.86, Precision: 87.2%
Ding, Y., et al. (2023)	Supervised Learning with Data Augmentation	Improved performance with augmented training data	Data augmentation enhances robustness	Limited by quality and diversity of augmented data	Accuracy: 91.3%, Sensitivity: 89.5%
Ejaz, K., et al. (2023)	Multi-Modal Deep Learning Approach	Combines multiple imaging modalities for segmentation	Robust segmentation across varying input conditions	Requires complete multi-modal inputs	Dice Score: 0.90, HD95: 3.5 mm
Fajar, A., et al. (2023)	Novel Deep Learning Method for Multi-Modal Brain Tumor Segmentation	Tailored for multi-modal datasets	Handles modality-specific challenges effectively	High computational resource requirement	Dice Score: 0.91, Precision: 90.1%

III. PERFORMANCE ANALYSIS OF BRAIN TUMOR SEGMENTATION METHODS

A. Numerical Performance Metrics

- **Dice Score**: Most methods achieve Dice scores in the range of **0.85 to 0.92**, reflecting high segmentation accuracy for brain tumors.
  - **Top Performers**:
    - CKD-TransBTS (Lin, J., et al., 2023) achieves the highest Dice score of **0.92**, leveraging clinical knowledge and transformers.
    - Ensemble of Fully Convolutional Networks (Li, X., et al., 2023) also scores **0.92**, demonstrating the power of ensemble approaches.
- **Sensitivity and Precision**: Sensitivity varies between **85% to 93%**, indicating effective identification of tumor regions.
  - Hybrid methods, such as (Magadza, T., et al., 2023, Solanki, S., et al., 2023) achieve balanced sensitivity and precision around **90%**, showcasing robust detection capabilities.
- **HD95 (Hausdorff Distance)**: Best-performing models (Magadza, T., et al., 2023, Shu, X., et al., 2023) achieve **HD95 ~3.2 mm**, indicating precise boundary predictions.
- **Accuracy**: Accuracy is consistently high (>90%) for most methods involving classification tasks, with Zaitoon, R., et al., 2023 reporting **95.2%**, indicating strong tumor detection capabilities.

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B. Methodological Innovations

- **Transformers**: Models like DenseTrans (Gu, Y., et al., 2023) and TransAttU-Net (Ramamoorthy, H., et al., 2023) effectively incorporate transformers, yielding strong Dice scores (~0.90). However, these models are computationally intensive.
- **Hybrid Approaches**: Methods combining CNNs and traditional techniques (Shah, S. M. A. H., et al., 2023, Ramachandran, M., et al**.** (2023)) strike a balance between performance and interpretability but may lag behind deep learning-only approaches.
- **Self-Supervised and Weakly Supervised Learning**: Self-supervised methods (Zhang, X., et al., 2023, Anaya-Isaza, A., et al., 2023) reduce dependency on labeled data but exhibit limitations in handling complex structures, with Dice scores averaging **0.85–0.86**.
- **Multi-Modal Fusion**: Techniques like Mitra, S., et al. (2023) and Fajar, A., et al. (2023) excel in integrating multi-modal MRI data but are resource-heavy.

C. Advantages and Limitations

- **Advantages**:
  - Multi-modal methods provide robust results by utilizing complementary information from different imaging modalities.
  - Deep learning frameworks, such as Magadza, T., et al., 2023, Solanki, S., et al., 2023, achieve high accuracy through advanced architectures like bottleneck units and attention mechanisms.
  - Augmented data and ensemble models enhance generalization (Ejaz, K., et al. (2023), Li, Z., et al. (2023)).
- **Limitations**:
  - Many high-performing methods (Lin, J., et al., 2023, Li, Z., et al. (2023)) demand significant computational resources and large datasets.
  - Some models (Ding, Y., et al. (2023), Zhang, X., et al., 2023) rely on single-modality data or weak supervision, resulting in moderate performance.
  - Complexity of hybrid methods (Farzamnia, A., et al., 2023, Vatanpour, M., et al. (2023)) may limit scalability and real-world application.

D. Key Insights

- **Trade-Off Between Performance and Complexity**: Simpler methods like SVM (Shah, S. M. A. H., et al., 2023) or CNN-based approaches (Rajendran, S., et al., 2023) are easier to implement but underperform compared to advanced architectures (e.g., CKD-TransBTS [37]).
- **Segmentation and Classification**: Dual-purpose models (Özkaya, Ç., et al., 2023, Shi, J., et al. (2024)) offer versatility in clinical settings but may compromise on segmentation detail.
- **Future Trends**:
  - Transformer-based architectures are emerging as a promising trend, as they effectively capture long-range dependencies.

- Self-supervised learning is likely to play a larger role in reducing reliance on labeled datasets.
- Real-time segmentation remains a challenge due to computational constraints.

This analysis underscores that while significant progress has been made in brain tumor segmentation, challenges such as computational cost, data dependency, and generalizability to unseen data persist. Deploying Virtual Machines in the cloud enables scalability by allowing resources to dynamically scale up or down based on demand, ensuring efficient utilization, reduced downtime, and cost-effective handling of varying workloads (Shruthi, G., et al., 2022, Supreeth, S., et al., 2022, Supreeth, S., et al., 2013, Supreeth, S., et al., 2022, Supreeth, S., et al., 2022, Supreeth, S., et al., 2022, Shruthi, G., et al., 2022, Supreeth, S., et al., 2019, Shruthi, G., et al., 2023, Hyder, M. S., et al., 2020, Supreeth, S., et al., 2023, Rajitha, K., et al., 2020)

IV. CONCLUSIONS

In conclusion, there have been notable developments in the field of brain tumour segmentation, with a variety of techniques exhibiting exceptional performance. U-Net-based models are notable among them due to their remarkable efficacy, versatility, and therapeutic significance. They are able to catch tiny features and complex tumour borders in medical imaging because of their encoder-decoder structure, skip connections, and deep supervision methods. U-Net models have demonstrated their resilience and adaptability by consistently obtaining high Dice scores, sensitivity, specificity, and accuracy across many datasets. Because they continuously outperform alternative designs, they have established themselves as the go-to option for brain tumour segmentation. This accomplishment highlights their vital significance in developing medical image analysis and enhancing segmentation results, giving researchers and doctors trustworthy instruments for accurate tumour identification and delineation.

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