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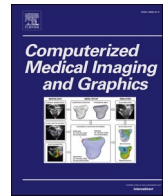
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A review on brain tumor segmentation based on deep learning methods with federated learning techniques

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ABSTRACT

Brain tumors have become a severe medical complication in recent years due to their high fatality rate. Radiologists segment the tumor manually, which is time-consuming, error-prone, and expensive. In recent years, automated segmentation based on deep learning has demonstrated promising results in solving computer vision problems such as image classification and segmentation. Brain tumor segmentation has recently become a prevalent task in medical imaging to determine the tumor location, size, and shape using automated methods. Many researchers have worked on various machine and deep learning approaches to determine the most optimal solution using the convolutional methodology. In this review paper, we discuss the most effective segmentation techniques based on the datasets that are widely used and publicly available. We also proposed a survey of federated learning methodologies to enhance global segmentation performance and ensure privacy. A comprehensive literature review is suggested after studying more than 100 papers to generalize the most recent techniques in segmentation and multi-modality information. Finally, we concentrated on unsolved problems in brain tumor segmentation and a client-based federated model training strategy. Based on this review, future researchers will understand the optimal solution path to solve these issues.

1. Introduction

The brain is called the central processing unit, which controls sensory information, blood pressure, respiratory system, releasing hormones, etc. There can be some abnormality due to behavioral action, which can be abnormal due to an accident, high blood pressure, or abnormal cells or tissues. Strokes, brain hemorrhages, and brain tumors are examples of prevalent disorders that occur nowadays. An estimated 251,329 persons died from primary malignant brain and CNS (Central Nervous System) tumors globally in 2020 (Brain Tumor: Statistics and Cancer, 2023). The tumor is formed when an unregulated cell appears, and there is no way to control this growth. In the central nervous system, abnormal cell respiration and proliferation lead to brain tumors. As a result, this cell rapidly multiplies and takes on the size of the brain area, essentially causing pressure and unconsciousness problems. If this tumor is not identified correctly, it might be fatal for patients. On the other hand, not all brain tumors are cancerous, but only malignant tumors. It

has been estimated that around 80% of them are malignant and 20% are benign (Louis et al., 2016). Brain tumors have an impact on the neurological system's function based on their growth rate and location. Depending on the severity and location of a brain tumor, several treatment options are available. The size of aberrant cells and tissues is extensive in the metastatic group, which might create any form of disease in the body. Recently, oligodendrocyte-based gliomas have attracted the attention of researchers (Abd-Ellah et al., 2016).

An image analysis technique is used in machine learning research to construct a system to classify the tumor's type. For research purposes, two paths are taken: classification and segmentation (Bauer et al., 2013). The segmentation approach may identify the tumor from pictorial data (pixel level). Segmentation is becoming an increasingly popular study topic in medical imaging analysis. Tumor or glioma diagnosis and therapy both heavily rely on image segmentation. Astrocytomas and oligodendrogliomas are the least aggressive and common gliomas, but HGG (GBM grade IV) is among the most destructive. High-grade gliomas

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cause more damage than lower-grade glioblastomas (Menze et al., 2015). Usually, gliomas are treated with surgery, chemotherapy, and radiotherapy. Early detection can help improve patient medical diagnoses and treatment policies. First and foremost, imaging data from the patient must be collected. There are numerous types of scanning available to detect abnormalities. Such methods are known as computed tomography (CT), X-ray, SPECT, PET, MRS, and MRI (Woźniak et al., 2023; Pfeiffer et al., 2007; Sebastian and Gnana King, 2022; Fink et al., 2015). Strong magnetism, electromagnetic radiation, and a computer are used in the MRI examination to produce a precise image (Jayadevappa et al., 2011).

An MRI imaging system analyzes four types of inputs to diagnose gliomas, including T1-weighted (T1), T2-weighted (T2), gadolinium-based contrast intensification (T1-Gd), and Fluid-Attenuated Inversion Recovery (FLAIR) shown in Fig. 1. It is also crucial to remember that the dataset is incredibly thick and intricate when the proper standard paradigm slices are joined for diagnostic purposes. T2 imaging is frequently employed to outline the inflammatory regions and provides a robust signal mainly on the image, whereas T1 imaging is typically utilized to differentiate endothelium (healthy tissues). It is easy to identify the tumor boundary with T1-Gd images because of the strong signal of the accumulating imaging technique (gadolinium ions). Necrotic cells can be distinguished from active cells in the same sequence because necrotic cells do not involve contrast material and can show up in hypo-intense tumor centers (Wadhwa et al., 2019; Menze et al., 2010). It is possible to discriminate between edema and cerebral edema in cerebrospinal fluid (CSF) using FLAIR images because the signal from water molecules is muted. A split tumor is essential before

beginning any treatment. Hence, good tissues are protected while malignant cells are destroyed. Finding, identifying, and isolating the active components of a brain tumor from healthy brain areas, such as the gray matter (GM), white matter (WM), and CSF, are all necessary steps in the segmenting process (Lau et al., 2019).

Based on this knowledge, many researchers worked on segmenting brain tumors, and the number of papers identified is displayed in Fig. 2. Deep learning approaches have recently demonstrated exceptional performance in brain tumor segmentation and classification (Lundervold and Lundervold, 2019). With the implementation of AI technology in the e-healthcare industry, there have been significant improvements in medical research, allowing domain specialists to give more effective medical services to the public. The development of deep learning, which combines AI and machine learning, has aided in the development of numerous state-of-the-art methods for identifying brain tumors and enabling the early detection of malignant tumors so that preventative measures can be implemented to save lives (Hinton, 2018). Deep learning produces less accurate findings when the training and testing datasets are smaller. To solve this problem, federated learning is utilized to train the shared global model with data from various organizations while maintaining data privacy (Ng et al., 2021; KhoKhar et al., 2022).

In a precise sense, the term "deep learning" refers to the implementation of artificial neural networks that incorporate multiple functional layers. Neural networks possess the capability to acquire complex hierarchical features in high dimensions and provide an approximation of continuous functions (Faysal Ahamed et al., 2023). Several surveys have discussed deep learning strategies developed in light of deep neural network accomplishments and new enhancements. Artificial

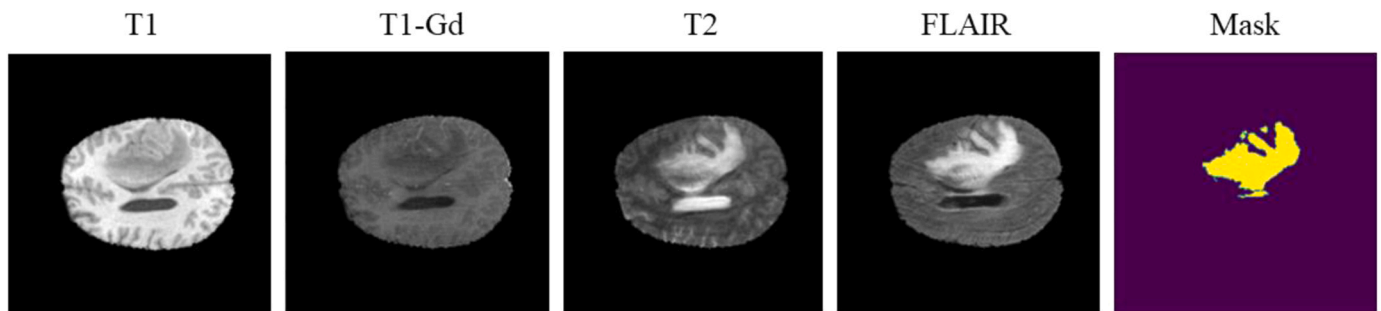


Fig. 1. This figure contains the four modality of MRI images (middle slice) such as T1, T1-Gd, T2, FLAIR, and mask categories.

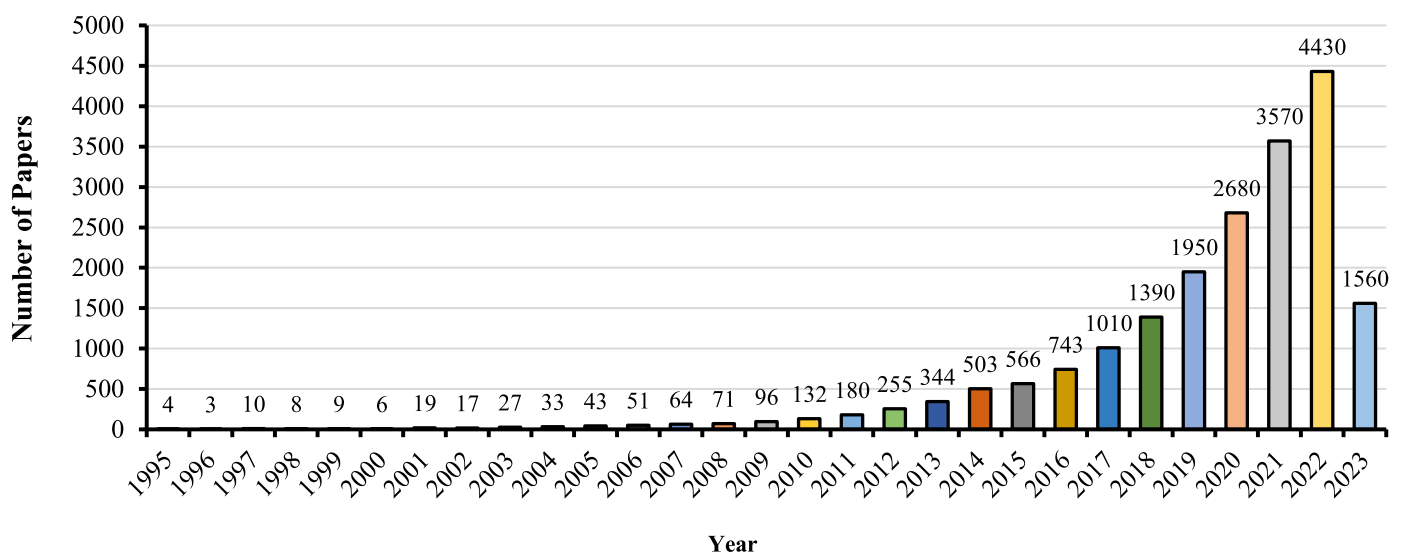


Fig. 2. The number of published papers on brain tumor segmentation using artificial intelligence in the corresponding year.

Table 1

The current literature on the subject of "brain tumor segmentation and Federated Learning" is listed here with limitations.

Paper Title	Publishing Journals	Contribution	Limitations
"Data Augmentation for Brain-Tumor Segmentation: A Review" (Nalepa et al., 2019)	Frontier Computational Neuroscience (2019)	Based on the impact of data augmentation, they proposed future research directions for generating high-quality artificial brain tumor examples to improve deep model generalization.	Focused only on augmentation technique and not provided any comprehensive analysis.
"A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned" (Abd-Ellah et al., 2019)	Elsevier (Magnetic Resonance Imaging) (2019)	Explored the principal accomplishments by scrutinizing the efficiency evaluation of the implemented algorithms.	Other emerging methodologies or alternative imaging modalities were not evaluated.
"Brain tumor segmentation of MRI images: A comprehensive review on the application of artificial intelligence tools" (Ranjbarzadeh et al., 2023)	Elsevier (Computers in Biology and Medicine) (2023)	Data augmentation were employed and how those methods impacted underlying supervised learners.	Multi-modality and federated learning analysis were not presented.
"An artificial intelligence framework and its bias for brain tumor segmentation: A narrative review" (Das et al., 2022)	Elsevier (Computers in Biology and Medicine) (2022)	Different architectures were examined, and performance matrices were measured by utilizing benchmarking performance bias.	Focused on risk-of-bias (RoB) in artificial intelligence (AI) architectures without analyzing the broader challenges and limitations of AI-based brain tumor segmentation techniques.
"A Review of Medical Federated Learning: Applications in Oncology and Cancer Research" (Chowdhury et al., 2022)	Springer (Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) (2022)	Provided a complete overview of federated learning, with a focus on cancer applications and methods.	Did not discuss about brain tumor segmentation on federated learning issues, and did not provide systematic direction on privacy analysis.
"Automated Brain Tumor Segmentation Using Multimodal Brain Scans: A Survey Based on Models Submitted to the BraTS 2012–2018 Challenges" (Ghaffari et al., 2020)	IEEE Reviews in Biomedical Engineering (2020)	Examined the development of an automated model through the utilization of multimodal MR images and proposed a benchmark by comparing others' work.	Discussed only a limited range of the dataset and missing modality information was not presented.
"A survey on brain tumor detection using image processing techniques" (K Kapoor and Thakur, 2017)	IEEE Explore (Data Science & Engineering) (2017)	Broke down the process of locating malignancies into four phases (pre-processing, segmentation, optimization, and feature extraction) from existing research from biomedical images.	Multiclass segmentation was not analyzed and state-of-the-art methodology was not presented clearly.
"A Survey of Brain Tumor Segmentation and Classification Algorithms" (Biratu et al., 2021)	MDPI (Journal of Imaging) (2021)	Provided an overview on segmentation and classification, three major techniques (region growing, shallow machine learning, and deep learning), various technical aspects such as strengths and weaknesses, pre- and post-processing techniques.	The section on architecture and multiclass segmentation was barely discussed and model performance degradation challenges did not analyzed.
"A review on federated learning towards image processing" (KhoKhar et al., 2022)	Elsevier (Computers and Electrical Engineering) (2022)	Highlighted federated learning architectures and emphasized its role in enhancing data security and privacy in image processing applications.	The privacy of medical data was not adequately addressed, the appropriate image processing algorithm was not thoroughly analyzed, and deep learning with federated learning was not directed properly.

intelligence has been largely successful in the diagnostic realm, but it remains challenging to construct an efficient model with small datasets in specific settings (Cui et al., 2018). To solve this problem, federated learning was used to train the global model at multiple sites simultaneously. Federated learning creates a global model by combining training results from multiple sites without direct data exchange. This paper focuses on the issues of federated learning in segmentation.

This research looks at the state-of-the-art segmenting of brain malignancies with MRI data, concentrating on foundational deep learning and federated learning algorithms. In addition, it offers a comprehensive review of the research on brain tumor detection and segmentation utilizing federated and deep learning methods. Recently, much research has been performed on deep learning for automated brain tumor diagnosis, but relatively few studies have been done on federated learning (Nazir et al., 2021; Zhou et al., 2023a). In this study, we present a systematic review of categories by combining deep learning and federated learning approaches. The popular benchmarking dataset is discussed here where the previous researcher worked and future researchers will get the proper direction. This research analyzes a wide variety of publicly available and privately held datasets to shed light on the outstanding problems and obstacles in the field of brain tumor segmentation.

The paper is divided into a total of seven sections. Section 2 presents a review of some relevant literature. Section 3 and Section 4 discuss

recent research challenges and advancements, respectively. Section 5 summarizes the study plan with the appropriate article identification, screening, and selection methods. Section 6 seeks to answer the research questions generated. Current clinical applications are discussed in Section 7. Finally, the main findings from this review are summarized in Section 8.

2. Literature Review

2.1. Survey of recent review papers

Recent relevant review papers are presented in Table 1, along with their respective details and highlights.

Nalepa et al (Nalepa et al., 2019). explored the advancements in data augmentation techniques for MRI on the BraTS 2018 dataset. The work highlights the potential for improving the effectiveness of algorithms for supervised learning through various data augmentation strategies. Additionally, it identifies exciting future research areas for synthesizing high-quality artificial brain tumor instances, which could enhance deep four models' generalization skills. The study focused on the BraTS dataset and explored the promising possibilities of the suggested technique. One potential positive aspect of this study is that it includes published image information.

To diagnose brain tumors, Abd-Ellah et al (Abd-Ellah et al., 2019). assessed both conventional and deep machine-learning techniques. They also examined significant accomplishments based on performance measurement metrics of the implemented algorithms in the three diagnosis stages. Furthermore, it highlighted the acquired knowledge as a guide for prospective investigations on the BraTS 2018 dataset. This review identified the significant accomplishments evidenced in the performance measurement metrics of the applied algorithms in the three diagnostic processes.

Ranjbarzadeh et al (Ranjbarzadeh et al., 2023). analyzed recent developments in data-augmentation methods used on brain tumor magnetic resonance images. It examined papers submitted to the Multimodal Brain Tumor Segmentation Challenge (BraTS 2018 edition) to see which approaches to data augmentation were used and how they affected underlying supervised learners. In order to improve the generalization capabilities of deep models, it suggests prospective research approaches for synthesizing high-quality artificial brain tumor cases.

Das et al (Das et al., 2022). employed a PRISMA methodology to classify 75 pertinent research works into four categories, namely convolutional neural network (CNN), encoder-decoder (ED), transfer learning (TL), and hybrid DL (HDL)-based architectures. This study analyzed 32 attributes related to artificial intelligence. It established a threshold for bias detection to categorize studies as having low, moderate, or high levels of bias. According to the performance ranking, TL architecture is superior, followed by ED, CNN, and HDL in descending order.

To determine the cutting-edge Federated Learning applications for oncology research and clinical analysis, Chowdhury et al (Chowdhury et al., 2022). conducted a systematic literature study. The study aims to present a comprehensive analysis of the developing Federated Learning field, with a specific emphasis on the employment of applications and algorithms in the field of oncology. Additionally, it will assist the readers in recognizing prospective requirements and forthcoming pathways for investigation and advancement.

The authors, Ghaffari et al (Ghaffari et al., 2020). conducted a comprehensive analysis of the development of automated models utilized for brain tumor segmentation through the integration of multimodal MR images. The study involved a comparison of various methods, and the proposed models were evaluated through their application to the well-known benchmark BraTS 2012–2018 challenges. Kapoor et al (Kapoor and Thakur, 2017). and Biratu et al (Biratu et al., 2021). directed their attention toward summarizing conventional techniques for brain tumor segmentation. Nevertheless, it was noteworthy that neither of them provided a comprehensive technical analysis or discourse on segmentation techniques based on deep learning.

KhoKhar et al (KhoKhar et al., 2022). provided an overview of the frameworks utilized in federated learning and examined their applications in machine learning, deep learning, and data mining. The study centered on how to use image processing techniques to safeguard and preserve the confidentiality of data trained on the model.

2.2. Scope of this survey

In this review, the findings from over a hundred scholarly papers have been compiled and summarized from renowned scientific databases like IEEE, Springer, Elsevier, MDPI, and Wiley. To ensure the preservation of high-quality research results in medical imaging, we reviewed the proceedings of major conferences such as ISBI, MICCAI, IPMI, MIDL, CVPR, ECCV, and ICCV. Many tasks and associated competition entries, such as the “Multimodal Brain Tumor Segmentation Challenge (BraTS)” were examined. In addition, the arXiv library was included for better information retrieval.

The primary objective of this review is to provide an in-depth study of brain tumor segmentation using a combination of deep learning and federated learning models. More research must be carried out on

federated-based segmentation to enhance its effectiveness. Any errors in spelling, grammar, and punctuation have been corrected. Therefore, it is essential to make a systematic and strategic review to obtain a suitable novel research direction. This study is intended to find out how different architectures affect the segmentation of brain images and give a direction on patient data handling by utilizing federated learning concepts in a wide range of brain image datasets. Advanced topics, including dataset benchmarks, segmentation of techniques, and multimodal procedures, are also addressed. Finally, the review presents unresolved issues and potential paths for further study.

2.3. Contribution of this survey

The main contributions of this study are as follows.

- According to our knowledge, this is the first comprehensive survey paper that combines the categorization of federated learning algorithms and deep learning models to segment multiclass brain tumors.
- A systematic review is presented in which various recent methodologies for brain tumor segmentation are discussed.
- The best deep learning segmentation methodologies are identified through multiclass tumor recognition comparison.
- The process flow, beginning with the planning phase, is briefly discussed, as are challenging segmentation data issues.
- We thoroughly compare various modality issues with effective solutions to extract features from both modality and missing modality information.
- A federated learning process is designed to keep data private on both client-side and server-side systems. These systems can keep both small and large datasets to improve the model’s performance.

3. Research challenges

Numerous scholars have attempted to identify the optimal approach for image segmentation. Based on current research, it is evident that deep learning-based models exhibit superior performance compared to the others. However, it should be noted that there are some challenges to achieve improved results in both research and clinical implementation (Havaei et al., 2017). Several researchers tried to remove those anomalies and achieve greater accuracy. Based on the constraints, the challenges are categorized as follows.

3.1. Location Uncertainty

Location confusion means that it is hard or impossible to know where a tumor is exactly in brain. Brain tumor segmentation is a difficult job that requires pinpointing the exact location of the tumor because of differences in tumor size, shape, and location, as well as differences in the quality and clarity of imaging data (Kao et al., 2020). This confusion can affect how well segmentation and treatment planning work. Different ways have been suggested to deal with location uncertainty in brain tumor segmentation, such as using multimodality data can help to find the shape and position of the tumor.

3.2. Morphological Uncertainty

The inability to precisely define the boundaries of tumors is known as morphological uncertainty. Due to the prevalence of HGG and LGG cases and their penetration into neighboring tissues, it may be challenging to distinguish tumor tissue from normal brain tissue (Jungo et al., 2018). The outer layer of a brain tumor is composed of edema tissues, which exhibit a variety of fluid configurations that make it difficult to establish a baseline for describing the tumor’s contours. Due to this uncertainty, tumors may be incorrectly segmented, which might impede diagnosis and treatment.

3.3. Low Contrast

Low-contrast pictures are those in which the contrast between the tumor location and the surrounding normal brain tissue is so low that radiologists or computer algorithms struggle to detect and segment the tumor appropriately. This may happen because of the MRI scan's imaging settings or the tumor's size, location, or type (Dubey et al., 2011). Low-quality and low-contrast MRI images might result from the projection and tomography procedures. Imaging abnormalities, such as noise or motion artifacts, can also contribute to low contrast, masking crucial elements in the picture.

3.4. Annotation Bias

The term "Annotation Bias" relates to the challenge of manually segmenting tumor locations when the annotations supplied by different radiologists or medical professionals differ. Variations in individual backgrounds, comprehension, or subjective predispositions may explain the observed phenomenon. The generated annotations may contain inconsistencies or mistakes, offering potential issues in the training and evaluation of deep-learning models for tumor segmentation (Kim et al., 2023). To address this issue, it is critical to get a diverse and comprehensive collection of annotations from various specialists, as well as to painstakingly authenticate and correct the annotations to ensure their precision and uniformity.

3.5. Imbalanced Issue

An uneven number of pixels or voxels in the dataset that belong to the different classes causes "imbalance issues" in peritumoral edema, GD-enhanced, and NCR/ECT region segmentation. It is common in medical image analysis to discover that one class (such as the backdrop) has far more pixels or voxels than the classes of interest (such as tumor patches) (Rezaei et al., 2019). Large tumor regions may have a considerable impact on the retrieved characteristics, which influence the data-driven learning technique. It leads to a bias in training for the majority class and poor performance in recognizing the minority class. To overcome this issue, several strategies have been proposed in the literature, including oversampling, under-sampling, and class weighting.

3.6. Lack of clinical implementation

Despite rapid development in medical imaging and AI, there is a noticeable absence of software engineering in the healthcare industry, especially regarding cutting-edge software development dedicated to disease diagnosis (Kernbach et al., 2022). Although modern ML and DL methods have shown high accuracy in detecting brain tumors, medical professionals such as doctors, radiologists and clinicians exhibit a degree of skepticism towards using the modern technology due to their lack of understanding on the black box prediction process involved in the disease diagnosis. This forces them relying more on their astute observations and traditional manual methods (Verdicchio and Perin, 2022). Explainable AI (XAI) has showed considerable potential in healthcare, allowing the clinicians and other relevant stakeholders to gain transparent insights into intricate decision-making processes (Borys et al., 2023). This, in turn, can lead to improved patient outcomes and contribute to the overall effectiveness and ethicality of the healthcare system. Furthermore, the communication gap exists between the software engineers and medical professionals. have yet to be bridged to properly implement AI technology in the medical IT infrastructure.

4. Progress in the past decades

Fig. 3 displays significant scientific progress in brain tumor segmentation and federated learning. This progress is represented based on the topmost work of the concurrent years to get a proper direction for improvement in this field. This representation is split into two parts: the first uses traditional machine learning, and the second uses deep learning algorithms. Zhu et al (Zhu and Yan, 1997). (1997) created a Hopfield neural network alongside active contoured shapes to extract the boundary of a tumor and outline the corresponding region. The limitations of computational capacity significantly restricted the training process. Since 1998, scholars have directed their attention toward conventional machine-learning models in order to achieve improved outcomes in the process of tumor segmentation. Clark et al (Clark et al., 1998). conducted a multispectral histogram analysis to differentiate the potentially malignant tumor from the surrounding intracranial area. A technique known as ATmC (Adaptive Template Moderated Classification), developed in 1999 by Kaus et al (Kaus et al., 1999)., was used to design surgical procedures integrating computers. In 2003, a study conducted by Resnick et al (Resnick et al., 2003). aimed to investigate the longitudinal MRI scan data of older people in order to determine regional pattern behavior. Prastawa

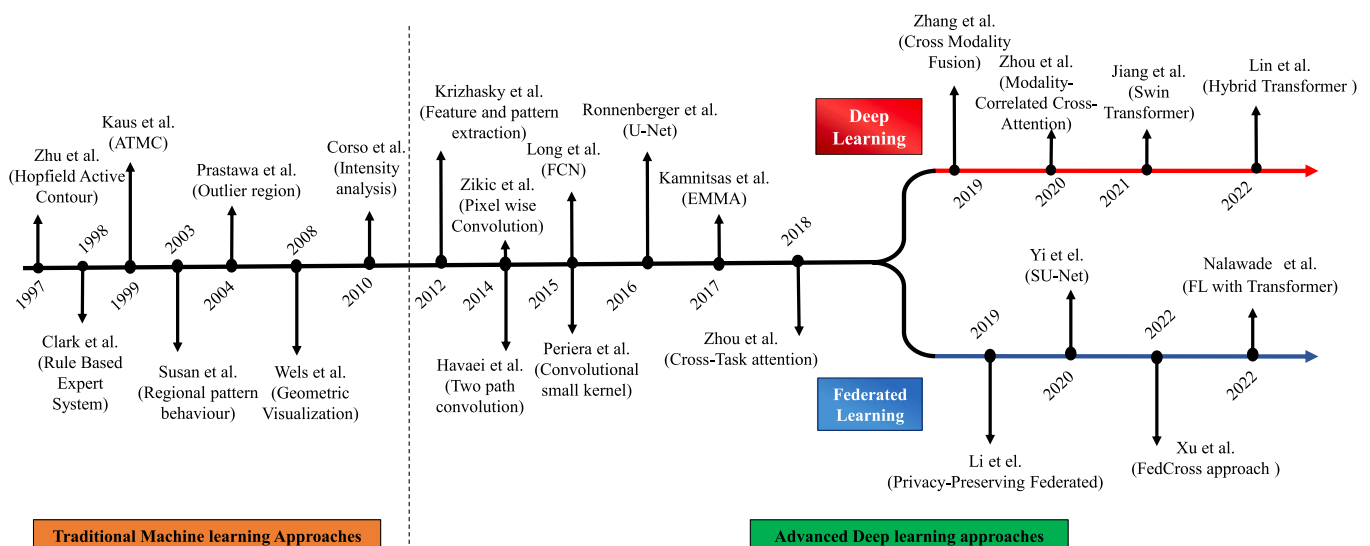


Fig. 3. The process flow, beginning with the planning stage and continuing up to the present, along with the year that corresponds to each stage.

et al (Prastawa et al., 2004). developed a framework with the intention of determining the outlier region based on the segmentation results. The results obtained from the latent atlas indicated superior outcomes in terms of intensity variation analysis through the histogram (Corso et al., 2008), geometric visualization (Wels et al., 2008), and detection of tumor regions (Menze et al., 2010). The initial work was at the forefront of utilizing machine learning techniques to address the segmentation challenge. Nevertheless, the initial studies exhibit noteworthy limitations. Initially, most early works concentrated solely on segmenting the entire tumor region, resulting in a segmentation outcome comprising a single category. Previous studies were based on stringent constraints and impractical assumptions. The process of manually devising characteristics is constrained by incompletely generalizable prior knowledge. Lastly, it should be noted that initial research efforts did not adequately address specific challenges, such as ambiguity in appearance and inconsistent data distribution.

Researchers started concentrating on employing deep neural networks to tackle numerous practical challenges when deep learning technology made a breakthrough. The principal benefit of deep learning resides in its capacity to acquire intricate, non-linear associations between input and output variables. Deep learning models can acquire features and patterns from unprocessed data in an automated manner, thereby eliminating the requirement for manual feature engineering. The capacity of deep learning to scale with larger data sets is another advantage (Krizhevsky et al., 2017). To accomplish precise brain tumor segmentation, state-of-the-art research efforts aim to develop specialized deep convolutional neural networks (Havaei et al., 2017; Zikic et al., 2014; Pereira et al., 2016). Recent methods for brain tumor segmentation take advantage of the improvements made possible by fully convolutional networks (FCNs) (Long et al., 2015) and U-Nets (Ronneberger et al., 2015) by building encoder-decoder relationships without fully connected layers.

Data imbalance is a problem resulting in a decline in the model performance. To deal with this problem, the researcher attempts to implement a cascaded-based network and ensemble process. Multitask learning, customized model layers, customized loss functions, and utilizing the information from multimodality help to overcome this. Modality fusion is also an effective process which deals with the missing values of modality. To describe 3D brain tumor semantic segmentation, Jiang et al (Jiang et al., 2022). developed an advanced model by combining with transformer, CNN, and encoder-decoder structure to define the 3D brain tumor semantic segmentation. Lin et al (Lin et al., 2023). designed a clinical knowledge-based segmentation model where dual branch autoencoder is used to reconstruct the brain tumor image. The model's efficacy deteriorated due to a problem with the data imbalance. Researchers are experimenting with cascade-based networks and ensemble procedures to address this issue (Kamnitsas et al., 2018; Jiang et al., 2020). To get around this, multitasking learning, modified successive layers, adapted loss functions, and making use of multimodality's information are all found to be helpful (Zhang et al., 2021a; Zhou et al., 2020a). Another efficient method for addressing the modality's missing values is called "modality fusion" (Zhou et al., 2021).

The restrictions from the governing rules on protecting medical data make it frequently impossible to gather and distribute information about patients. The challenge of accessing patient data is circumvented through the implementation of federated learning, which involves the deployment of programs that exchange only partial updates of the model training process among them. On the BraTS dataset, Li et al (Li et al., 2019a). constructed and evaluated the realistic federated learning algorithms for brain tumor segmentation. The SU-Net model for federated learning demonstrated improved efficiency (Yi et al., 2020). Xu et al (Xu et al., 2022). introduced the FedCross approach to counteract the decline in model aggregation performance during non-IID (non-Independent and Identically Distributed) data training. The performance and privacy of a federated-based model are improved by using a cascaded transformer in this paper (Nalawade et al., 2021).

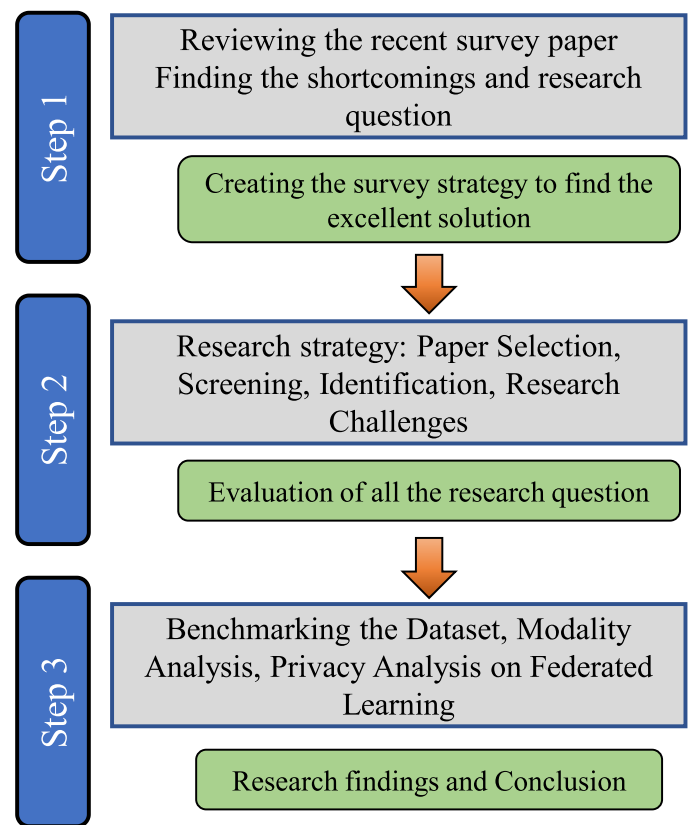


Fig. 4. Primary steps for systematic literature review.

5. Review strategy

This systematic literature review (SLR) aims to classify the recent approaches to segmenting the tumor as outlined in Fig. 4.

5.1. Research questions

One of the most essential parts of a review paper is developing a research question. This is because the question helps determine the scope and focus of the literature review. A well-written research question ensures that the review is structured, comprehensive, and pertinent to the subject under investigation. The creation of a well-defined research question can help with the identification and selection of pertinent articles for a review paper. This can help reduce the chance of bias in the selection process and ensure the review is a complete and fair summary of the available literature. Furthermore, formulating a research inquiry serves to structure the literature review and furnish the audience with a background. It can help the reader understand why the review is being done, how much of the literature is being looked at, and what the most important results and conclusions are. Zou et al (Zou et al., 2022)., presented a strategy to identify solutions to specific inquiries employing published research. The main objective of this research is to provide a comprehensive overview of contemporary brain tumor segmentation techniques utilizing deep learning and federated learning. Table 2 presents the formulated research questions regarding the critical objectives.

5.2. Searching Strategy

A well-organized research study is required to efficiently extricate pertinent information while excluding irrelevant studies via a meticulously crafted search strategy. Only articles that presented novel techniques for segmenting brain tumors using deep learning were considered

Table 2

The primary research questions and objectives that are analyzed in this review paper.

RQ	Statement of Research Question	Objective
1	Which techniques are now thought to be the most effective for segmenting brain tumor?	The objective of this investigation is to analysis a technique by deep learning and federated learning methodologies.
2	What are the performance matrices utilized to assess the effectiveness of different diagnostic methods for brain tumors?	The aim of this investigation is to evaluate the efficacy of current state of the art approach.
3	What are the standard datasets that have been used in recent academic efforts to find ways to spot tumors?	This investigation's goal is to identify the benchmark datasets, together with available non-public and public datasets.
4	What is the impact on multi-modality information?	The primary objective is to enrich existing datasets by incorporating multiple sensory modalities in order to facilitate a more comprehensive understanding of the data.
5	What is the impact of privacy and performance on federated learning?	The main goal is to deal with the effects of privacy issues and performance problems by allowing joint model training on decentralized data.

Table 3

The keywords were used to find out the more relevant paper.

Digital Library	Searching keywords
IEEE Xplore	((“deep learning” OR “machine learning” OR “artificial intelligence” OR “federated learning”) AND (“glioblastoma,” OR “astrocytoma,” OR “brain cancer,” OR “brain tumor”) AND (“Segmentation” OR “Modality”)) Publication Year: 2016–2022
Science Direct	((“deep learning” OR “machine learning” OR “artificial intelligence” OR “federated learning”) AND (“glioblastoma,” OR “astrocytoma,” OR “brain cancer,” OR “brain tumor”) AND (“Segmentation” OR “Modality”)) Publication Year: 2016–2022
Nature	((“deep learning” OR “machine learning” OR “artificial intelligence” OR “federated learning”) AND (“glioblastoma,” OR “astrocytoma,” OR “brain cancer,” OR “brain tumor”) AND (“Segmentation” OR “Modality”)) Publication Year: 2016–2022
MDPI	((“deep learning” OR “machine learning” OR “artificial intelligence” OR “federated learning”) AND (“glioblastoma,” OR “astrocytoma,” OR “brain cancer,” OR “brain tumor”) AND (“Segmentation” OR “Modality”)) Publication Year: 2016–2022
Springer	((“deep learning” OR “machine learning” OR “artificial intelligence” OR “federated learning”) AND (“glioblastoma,” OR “astrocytoma,” OR “brain cancer,” OR “brain tumor”) AND (“Segmentation” OR “Modality”)) Publication Year: 2016–2022
ACM	((“deep learning” OR “machine learning” OR “artificial intelligence” OR “federated learning”) AND (“glioblastoma,” OR “astrocytoma,” OR “brain cancer,” OR “brain tumor”) AND (“Segmentation” OR “Modality”)) Publication Year: 2016–2022
Wiley	((“deep learning” OR “machine learning” OR “artificial intelligence” OR “federated learning”) AND (“glioblastoma,” OR “astrocytoma,” OR “brain cancer,” OR “brain tumor”) AND (“Segmentation” OR “Modality”)) Publication Year: 2016–2022

for inclusion in this systematic review. From January 1, 2016, through December 30, 2022, we combed the digital archives of Elsevier, ACM, IEEE, Springer, MDPI, Wiley, and MICCAI for papers that fit our criteria. [Table 3](#) presents the search strings that were employed for the repositories, encompassing primary, secondary, and supplementary keywords.

5.3. Study screening criteria

This article highlights a subset of the research literature in keeping with the study's aims while ignoring the large body of literature that does not contribute to those aims. To filter relevant publications, Naeem et al ([Naeem et al., 2020](#)). 's search strategy was utilized. This technique required the use of precise search terms in order to locate articles that met a set of criteria. Based on precise screening criteria, articles that did not match the requirements were eliminated. Through screening, only the most relevant publications were selected for inclusion in the study. Using credible and pertinent sources, the study's quality was validated. We did not include some study articles because they did not meet the following rules:

- Research papers that do not use or look at datasets that are available to the public for brain tumor segmentation
- Research studies without performance measures like dice score, jaccard score, specificity, and sensitivity.
- Research papers that do not explain how deep learning or federated learning works.
- Articles on segmentation that are unrelated to medical imaging or brain tumors.

- Research papers that have not gone through peer review.

5.4. Selection process

This section describes how relevant publications were identified for this survey inquiry. The preceding section supplies the keyword string used to perform the search. After collecting many papers, a filtering process was conducted to ensure that only the most pertinent articles were extracted. The filtering procedure considered several parameters. In the initial stage, publications that matched the keywords were searched. In the second stage, only articles with acceptable names for segmenting brain tumors were selected. In cases where multiple titles were identified, the most recent article was selected based on the state of the art—the final step involved evaluating the development of the selected papers based on their abstracts and datasets. In the fourth step, a full-text-based analysis was conducted that provided insight into the advancement in this field. Attention was then concentrated on the references and contributions to ensure that no essential research publication was missed. A careful review of the references resulted in the addition of three more publications, bringing the total number to 73, as seen in [Fig. 5](#).

5.5. Data analysis and results

This section provides a concise summary of each study and a detailed analysis of its advantages and disadvantages. A summary of each study is also provided in a tabular format to provide a quick overview of the investigations and aid the reader in quickly comprehending the most essential aspects of each study. Examining the strengths and weaknesses

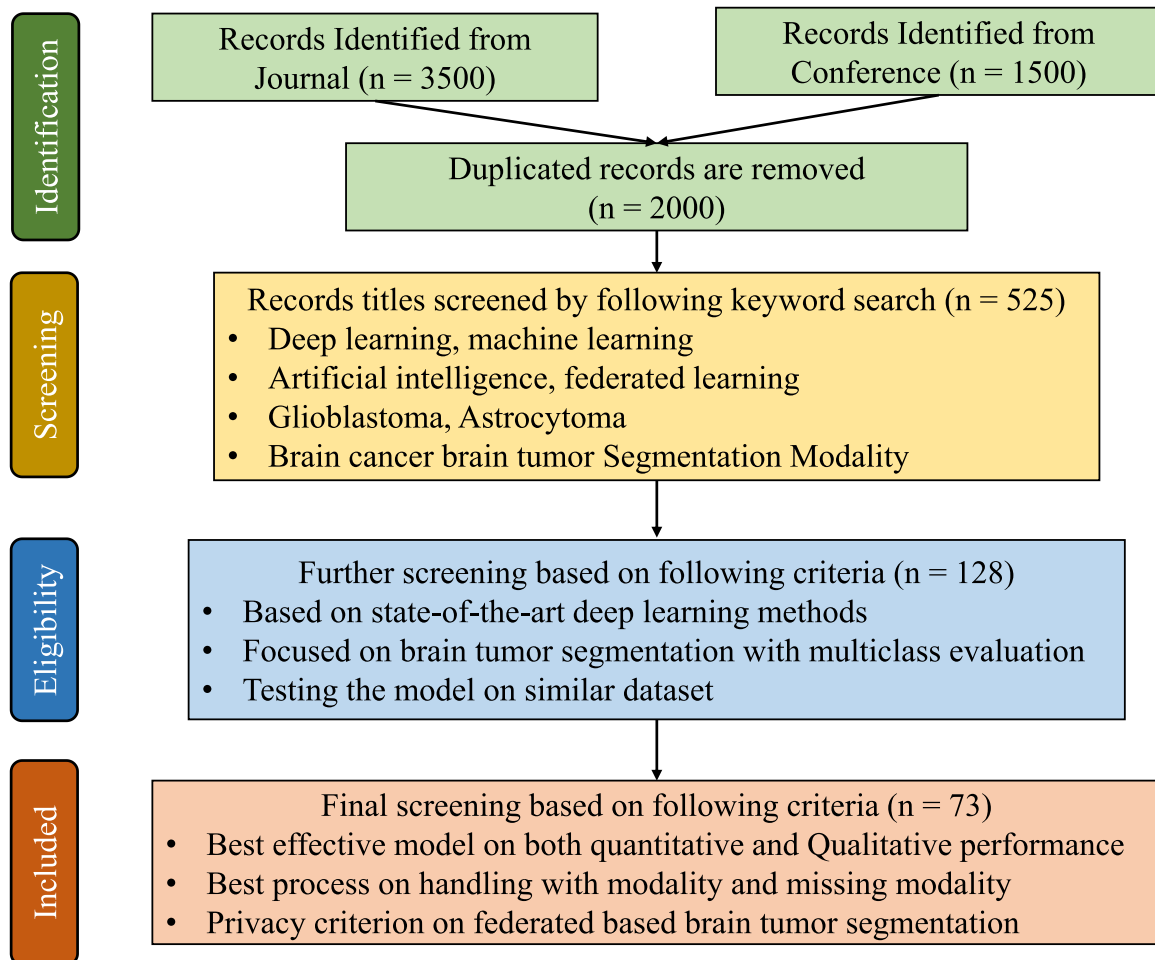


Fig. 5. The number of identifications, screening, eligibility, and selection processes are presented here.

of each study provides a deeper understanding of the research discipline. Tables 4 to 11 provide a comprehensive overview of the research, including its objectives, methods, and results, enabling readers to compare and evaluate it with other studies. This review analysis selected 73 publications from diverse sources, including journals and conferences. Using bar graphs, Fig. 6a illustrates the various repositories (IEEE, ACM, Springer, Wiley, Science Direct, etc.) from which the collected papers originated. Fig. 6b depicts the distribution of articles from various archives. These diagrams provide a graphical representation of the data that assists in understanding the distribution of the paper's sources.

6. Evaluation of research questions

The findings of the research questions set in Section 5.1. are analyzed here.

6.1. Most effective technique for classifying brain tumor

The main goal of image segmentation is to divide a picture into coherent parts based on criteria already set. The primary objective of brain tumor segmentation is to differentiate between the various types of tumor tissue, such as edema, necrosis, active tumors, and normal brain tissue. This study looked at individual questions by combining information from different studies. The goal was to discover how deep learning and federated learning are used to identify tumors. Convolutional neural networks (CNNs), the U-Net, and the Mask R-CNN are some of the most robust deep-learning methods for segmenting brain tumors (Milletari

et al., 2016). For optimal analysis, the papers were separated into four categories: pre-trained architecture, cascaded architecture, ensemble techniques, and federated learning. In addition, medical imaging research initially utilized conventional machine learning techniques, such as threshold leveling for local global regions, supervised segmentation methods, or pixel-to-pixel based techniques, such as artificial neural networks, K nearest neighbor techniques, random forests, support vector machines, super pixel-based segmentation, etc. Unsupervised techniques are also widely used, with clustering-based, density-based, K-means, and FCM clustering being the most common traditional approaches. For improved outcomes, hybrid techniques such as multi-modal fusion, deep learning with traditional algorithms, multi-scale and multi-resolution methods, and ensembling processes are utilized. Recently, deep learning models have generated significant results and enhanced performance. These deep learning methods consist of CNN, FCN, and U-Net, as well as top-down and bottom-up approaches. Significant research initiatives that employ innovative techniques are discussed below.

6.1.1. Pre-trained architecture

Nodirov et al (Nodirov et al., 2022). used 3D medical imaging data to develop more precise brain tumor segmentation models than 2D. They focused on prevalent 3D segmentation models such as 3D U-Net and V-Net. They employed 3D imaging data and devised a novel framework utilizing a 3D U-Net model that integrates cost-effective pre-trained 3D MobileNetV2 blocks and attention modules. The utilization of skip connections and attention modules facilitated the preservation of feasible model size and enhanced precision by optimizing feature extraction and eliminating extraneous features.

Table 4

The contribution, training algorithm, datasets and limitations of the most used segmentation methods for brain tumor MR images utilizing pre-trained method.

Contribution	Training Algorithm	Datasets	Limitations	Ref.
A power-efficient computing model that uses the MobileNetV2 backbone and attention modules to get the fastest and most accurate reasoning time.	3D U-Net + MobileNetV2	BraTS 2020	The testing results had some quality problems, like missing parts of the label and lower quality because the MobileNetV2 backbone was used, which needs a lighter network structure. For future development, the authors plan to look into other power-efficient architectures.	(Nodirov et al., 2022)
Using test-time enhancement to improve automated segmentation from various classes of brain tumors	DCNN	BraTS 2018	They did not explain how model is designed and implemented and qualitative performance is not mentioned properly.	(Wang et al., 2019a)
On the foundation of the U-Net design, an effective 2D convoluted network is created.	U-Net + Resnet50	BraTS 2015	Only cross-validation has been used to test the segmentation approach, and numerous network parameters still need to be fine-tuned.	(Dong et al., 2017)
Evaluated the deep learning model on various BraTS datasets.	DLM	BraTS benchmark	Only known meningiomas are used in segmentation studies; unknown testing sets are not considered.	(Laukamp et al., 2019)
Reduce overfitting, speed up training, and optimize parameters with the RELM classifier and a grid search method.	EL	CE-MRI	They did not perform any tumor regional extraction.	(Gumaei et al., 2019)
Designed a U-Net architecture with two sequentially connected network	U-Net	BraTS 2019	Model is not tested on multiple sources and mask prediction only showed for HGG samples.	(Kotowski et al., 2020)

Wang et al (Wang et al., 2019a). employed deep convolutional neural networks (CNNs) and used data augmentation at both training and test time to get satisfactory results. The purpose of this research was to examine how various network architectures and image augmentations, such as 3D rotation, flipping, scaling, and adding random noise, might improve the accuracy of CNNs during test-time augmentation. Experiments performed on the BraTS 2018 training and validation set show that test-time enhancement improves segmentation accuracy and uncertainty estimates.

Dong et al (Dong et al., 2017). created an autonomous approach for segmenting brain tumors via deep convolutional networks that were based on the U-Net. They discovered that their technique delivered correct segmentation efficiently. They tested it on the BRATS 2015 dataset, which contains both high-grade and low-grade tumors.

Laukamp et al (Laukamp et al., 2019). aimed to evaluate the efficacy of a multipara metric deep-learning model (DLM) for the automated detection and segmentation of meningiomas in routine MRI data from various sources. The results of the study indicated that the DLM exhibited high levels of accuracy, thereby suggesting its potential utility in facilitating therapy planning and monitoring of meningiomas.

Gumaei et al (Gumaei et al., 2019). proposed a novel approach for classifying brain tumors by combining an integrated feature collection technique with a regularized extreme learning machine (RELM). They employed the hybrid model to extract tumor features from the pre-processed brain pictures, followed by RELM to classify the tumors. On a public dataset of brain scans, their suggested method was tried, and it was discovered to be more successful than current state-of-the-art approaches, with increased classification accuracy.

Kotowski et al (Kotowski et al., 2020). employed a cascaded U-Net framework to identify and segment brain tumors, specifically low- and high-grade gliomas, from magnetic resonance imaging scans. Initial experiments conducted on the BraTS'19 validation dataset indicate that this methodology produces precise tumor demarcation and prompt segmentation. In Table 4 showed the contribution and the major limitation of pretrained architecture.

6.1.2. Cascaded Methods

In order to enhance the segmentation of MRI brain pictures, Aranguren et al (Aranguren et al., 2021). suggested a new method known as the LSHADE optimization algorithm. As a result of the significant unpredictability and complexity of brain pictures, the proposed method aimed to increase the segmentation accuracy of existing approaches. They used intensity normalization and skull stripping on the brain images as the first processing steps toward this end. The brain scans were then segmented into several tissue types using a fuzzy C-means

clustering technique. These tissue types include gray matter, white matter, and cerebrospinal fluid. They used Web (synthetic T1-weighted), IBSR18 (18 T1-weighted), and LPBA40 (40 T1-weighted) datasets.

In order to maximize the multi-level thresholding procedure, Tarkhaneh et al (Tarkhaneh and Shen, 2019). devised a novel method for segmenting MRI brain images. This method uses an ADE, or adaptive differential evolution algorithm. The authors tested their method using multiple open-source benchmark datasets and compared the results to existing state-of-the-art approaches. The outcomes demonstrated that their method obtained greater segmentation precision and robustness than thresholding-based methods. The authors also proposed an adaptive mechanism to enhance the performance of the ADE algorithm by adjusting the mutation and crossover rates based on population diversity and convergence status. Medical diagnosis and treatment planning may benefit from the proposed method.

Ozyurt et al (Ozyurt et al., 2020). came up with a way to find brain tumors that uses fuzzy C-means (FCM) clustering with super-resolution (SR) and a convolutional neural network (CNN) with an extreme learning machine (ELM). The first stage of the proposed system segments the MRI images and enhances their resolution using FCM clustering and SR. The segmented regions are then classified as tumors or non-tumors using a CNN with ELM in the second step. The authors tested their system on two open-source datasets and compared the results to those obtained using multiple state-of-the-art techniques. Their findings demonstrated that their proposed system was more accurate and efficient than competing approaches.

Amin et al (Amin et al., 2019). proposed a method for improving lesion scaling with the Weiner filter and several wavelet bands, as well as a method for brain tumor segmentation that employs various statistical methods. Comparisons between pixel-based and feature-based segmentation methods were performed. The pixel-based method involved identifying and comparing ground-truth annotations with examples of foreground and background pixels, as well as calculating error rate and quality. The local binary pattern (LBP) and Gabor wavelet transform (GWF) are extracted from each segmented image in the feature-based technique. The two texture traits were then combined to increase classification precision.

A novel deep learning technique for brain tumor segmentation that combined multiple kernel support vector machines (M-SVM) and kernel-based convolutional neural networks (KCNN) has been suggested by Thillaikkarasi et al (Thillaikkarasi and Saravanan, 2019). The suggested procedure entailed multiple phases, including tumor segmentation, feature extraction, classification, and image preprocessing. The MRI picture was initially improved and smoothed using adaptive histogram

Table 5

The contribution, training procedure, datasets and limitations of the most used segmentation methods for brain tumor MR images utilizing cascaded methods.

Contribution	Training Algorithm	Datasets	Limitations	Ref.
Searching for the optimal values of the clustering parameters, which included the number of clusters and the fuzzifier parameter.	Local Search Differential Evolution (LSDE)	BrainWeb, IBSR18, LPBA40	These characteristics include a lack of generality, interpretability, computational intensity, and reliance on preprocessing processes. The method might not be appropriate for real-time or high-throughput processing and might suffer from artifacts or poor image quality.	(Aranguren et al., 2021)
The proposed method can successfully partition brain tissues in MRI images and could be used in medical diagnosis and therapy planning.	ADE + multi-level thresholding	ABIDE	ADE algorithm may not always converge to optimal solution, leading to overfitting or underfitting in some cases.	(Tarkhaneh and Shen, 2019)
help to detect and diagnose brain cancers early, improving patient outcomes.	FCM+SR CNN+EL	BraTS 2015	It takes a lot of computing power and time to process, which may make it hard to use in real-time clinical situations.	(Özyurt et al., 2020)
Applying triangular fuzzy median filters helped achieve accurate segmentation, while the ELM algorithm was utilized to classify the data.	Fuzzy + ELM	BraTS 2012, 2013, 2014, 2015	Manual feature selection is required, which can be time-consuming and may reduce the method's repeatability.	(Amin et al., 2019)
To improve efficiency, a method is provided that integrates CNN, M SVM, and Kernel.	CNN + SVM	Local 40 MRI data	lack of explanation regarding the feature extraction process, and the model is not tested on benchmark datasets.	(Thillaikkarasi and Saravanan, 2019)
Semantic segmentation on 3D brain tumor input by following encoder and decoder approach.	3D CNN with encode decoder	BraTS 2019	Computational complexity is not discussed.	(Myronenko and Hatamizadeh, 2020)
CNN is used for classification, and the watershed method is used for segmentation.	CNN + watershed	Private dataset	Benchmark datasets that are open to the public are not used to evaluate the performance of the model, and multiclass results are not determined.	(Pathak et al., 2019)

Table 6

The contribution, training procedure, datasets, and limitations of the most used segmentation methods for brain tumor MR images utilizing ensemble techniques.

Contribution	Training Algorithm	Datasets	Limitations	Ref.
The tumor areas are effectively detected by the CNN and PNN models.	CNN + PNN	BraTS 2013	Model ensembles are not evaluated for multiclass segmentation.	(Madhupriya et al., 2019)
CNN with a diffusion filter removes noise, and OTSU finds out the appropriate threshold value for adaptive swarm optimization.	CNN + OTSU	IBSR + MS dataset	The suggested strategy was not thoroughly compared in the research with the most recent techniques for segmenting brain tumors.	(Vijh et al., 2020)
EMMA improves the multiclass segmentation results both quantity and qualitatively.	EMMA	BraTS 2017	The paper lacks clinical validation and does not provide insight into how the proposed technique performs in real clinical situations	(Kamnitsas et al., 2018)

equalization with contrast limitation (CLAHE) and Laplacian Gaussian filtering, respectively. Then, depending on the tumor's size, shape, epidermal attributes, and other parameters, feature extraction was carried out. The M-SVM was utilized for analyzing images based on the specified characteristics.

Myronenko et al (Myronenko and Hatamizadeh, 2020). used BraTS 2019 to investigate 3D semantic segmentation of brain tumors. They concentrated on optimizing automated approaches and investigated traditional encoder-decoder designs with incorporated loss functions to improve segmentation accuracy.

Pathak et al (Pathak et al., 2019). proposed a deep learning-based method for the automatic detection and segmentation of brain tumors. A convolutional neural network (CNN) classified a brain MRI image to ascertain the presence of a tumor as the system's input. If a tumor is detected, the proposed method segments and calculates its area using marker-based watershed segmentation and morphological operations. The experimental results indicate that the proposed method achieves a 98% accuracy rate with minimal computational complexity. Table 5 shows the contribution and the major limitation of cascaded methods.

6.1.3. Ensemble Networks

The goal of the machine learning technique known as ensemble classification is to improve the accuracy and resilience of the model by combining the predictions of several different classifiers into a single set. The core idea behind ensemble classification is to leverage the unique capabilities of several different models and use them in such a way that they exploit each other's weaknesses. Table 6 shows the contribution and the major limitation of ensemble networks.

Madhupriya et al (Madhupriya et al., 2019). presented a solution utilizing deep learning methodologies. The goal was to customize the treatment for both high and low-level tumor grades. Uncertainty in tumor characteristics, including size, shape, and contrast, presented a problem that required creative thinking to solve. The study employed convolutional neural networks (CNN) and probabilistic neural networks (PNN) architectures as a means of segmenting abnormal tissues within the brain. The CNN architecture proposed in this study utilized 3×3 and 7×7 overlapped convolutional layers.

Additionally, a cascaded architecture was devised to attain precise and efficient tumor segmentation. The PNN architecture was employed in tumor detection, and a comparative analysis was conducted between the outcomes of the CNN and PNN architectures. The researchers devised distinct convolutional neural network (CNN) and probabilistic neural network (PNN) structures to address local and global characteristics. The Brats13 image dataset was utilized to assess the efficacy of the proposed solution.

Vijh et al (Vijh et al., 2020). utilized adaptive particle swarm optimization and the OTSU thresholding method to determine the optimal threshold value. Anisotropic diffusion filtering is applied to the brain MRI images to improve image quality and remove noise. 101 MR pictures were used to test the suggested approach, which was confirmed to be trustworthy. The extracted features are used to train a convolutional neural network (CNN) for feature extraction. According to the results, ensemble classifiers performed better on large datasets since additional data increased the precision of the model.

For reliable segmentation of brain tumors, Kamnitsas et al (Kamnitsas et al., 2018). investigated the use of Ensembles of Multiple Models

Table 7

The contribution, training procedure, datasets, and limitations of the most used segmentation methods for brain tumor MR images utilizing federated learning strategy.

Contribution	Training Algorithm	Datasets	Limitations	Ref.
With federated learning models, the SU-Net provides a fast and private way to do segmentation tasks.	SU-Net + FedAvg	TCGA-GBM Dataset	Model evaluation at testing set and multiclass segmentation was not performed.	(Yi et al., 2020)
This study demonstrates a deep learning model's capacity to achieve good performance in federated semantic segmentation while protecting patient data privacy.	DL + FL	Multiple organization	They didn't look into how changing the number of institutions that took part affected how well the model worked, and it's not clear if the proposed method would work as well for other kinds of medical imaging employment.	(Sheller et al., 2019)
Analyzing the privacy of patient's data using deep learning by combining federated approach	DL + FL	BraTS 2018	One problem with this study is that the methods used to protect privacy could make the model less accurate.	(Li et al., 2019a)
Proposed framework is a promising way to use data from multiple institutions to improve MR image reconstruction without putting patients' privacy at risk.	DL+ FL	Multiple Dataset	Access to the target site's data is required for the suggested cross-site modeling approach, which may not always be possible.	(Guo et al., 2021)

and Architectures (EMMA). They explained how convolutional neural networks (CNNs) have repeatedly outperformed older techniques on complex tasks like dense semantic segmentation. However, the various proposed networks all operate differently, and architectural choices and training environments have a significant impact on their behavior. This research suggests utilizing EMMA to combine predictions from numerous approaches to solve this problem. The method lessens the risk of overfitting the configuration to a specific database and the impact of the meta-parameters of individual models.

6.1.4. Federated Learning Strategy

Federated learning (FL) revolutionizes healthcare by distributing the process of machine learning, enabling joint model development without the need to exchange raw data. Medical centers enhance models using their MRI scans and contribute only the learned information to a shared, more robust model. This approach promotes unbiased medical decisions and a better understanding of infrequent diseases through a broader spectrum of data. Globally, it promises consistent and superior clinical judgments, beneficial for isolated regions and uncommon illnesses. Initiatives like Health Chain and the Federated Tumor Segmentation are already harnessing FL for more accurate medical predictions and enhanced tumor identification (KhoKhar et al., 2022).

Despite the challenges of data privacy and scarcity in medicine, Yi et al (Yi et al., 2020). could segregate brain tumors using a federated learning model. The proposed SU-Net model integrated multi-scale receptive fields and information reuse using an inception module and dense blocks. Results show that SU-Net outperformed both the conventional U-Net and the cutting-edge semantic segmentation model DeepLabv3 + regarding AUC and DSC. The tests were conducted using the "Brain MRI Segmentation" dataset from the LGG segmentation at Kaggle. Even compared to baselines in the scenario of federated learning, SU-Net performed better.

Without exchanging patient data, Sheller et al (Sheller et al., 2019). suggested a method of cooperative deep learning for medical imaging. The authors addressed the ethical, technical, and legal issues surrounding the centralization of medical data sharing by using a federated learning strategy for multi-institutional collaboration. They found that federated learning performed better than two other collaborative learning methods when compared to their own. The performance of federated semantic segmentation models was comparable to that of models trained via sharing data, which assessed the performance of the proposed method on multimodal brain scans. This work showed that deep learning modeling is feasible for medical image segmentation without revealing patient data, which is helpful for cross-institutional research collaboration.

Li et al (Li et al., 2019a). directed their attention toward the issue of safeguarding privacy during the training of deep convolutional networks to segment cancerous tumors. The authors suggested using federated learning, in which the model training time intermediate model parameters were shared. However, sharing a model that was learned from patient data could indirectly reveal the local examples that were used to

train it. To solve this problem, the authors looked into whether or not differential privacy methods can protect patient data in a federated learning setup. They developed and assessed workable federated learning systems for segmenting brain tumors using the BraTS dataset, and they demonstrated a trade-off between model effectiveness and privacy protection expenses.

To speed up and improve the quality of MRI image reconstruction, Guo et al (Guo et al., 2021). proposed a deep learning-based approach. The suggested method used federated learning to take advantage of MR data available at different institutes while protecting patients' privacy. This is not very easy because of the enormous amounts of data involved. However, models trained with this method may only be able to be used in other places if the data was collected at different institutions using different acquisition methods. The authors developed cross-site modeling for MR image reconstruction to solve this problem. This technique aligned latent features at the intermediate level learned from several source sites with the distribution of latent features at the targeted site. The authors did many experiments to learn more about the federated learning approach to MR image reconstruction. Table 7 shows the contribution and the major limitation of the federated learning strategy.

6.2. Performance metrics used for assessing brain tumor identification

6.2.1. Multi-Class Tumor segmentation

There are many ways to figure out how well tumor segmentation occurs using different performance metrics. For instance, the researchers prioritized the dice coefficient score (Nazar et al., 2020). Some of the experts also figured out the Hausdorff scores (Bahadure et al., 2018). These are the primary evaluation criteria to figure out how well or accurately the model gets the tumor lesion. In tumor segmentation, it is usual to divide brain tumors into different regions. The WT, TC, and ET classes are often used. The above groups describe different sub-regions of the tumor that have different characteristics and are clinically important.

Whole Tumor (WT): The term "WT" refers to a kind of tumor that includes the tumor core and any edema around it. It provides a complete picture of the tumor's extent by including active tumor cells and cells infiltrating neighboring tissues.

Tumor Core (TC): The "TC" class denotes the center and most aggressive region of the tumor. It frequently contains the enhancing region, which corresponds to regions of aggressive tumor growth and increased vascularity. This classification is crucial for locating the cancerous cells most aggressive and resistant to treatment.

Enhancing Tumor (ET): The term "ET" refers specifically to a tumor's internal region that appears enhanced on contrast-enhanced magnetic resonance imaging (MRI). This area, which often represents the tumor's most rapidly reproducing portion, is crucial for therapy planning and monitoring.

In order to better characterize and understand the tumor, it must be segmented into three distinct classes. Treatment planning, evaluating

Table 8

Comparison of recent deep learning methods for brain tumor segmentation on various BraTS datasets, MRI modalities, dimensions, model architectures, evaluation metrics including loss function, dice coefficient (DSC), Hausdorff distance, mean sensitivity, mean specificity, and segmentation targets ("ET – Enhancing tumor; WT – Whole tumor; TC – Tumor core; and '-' Not available").

Papers	Dataset	Dim	Type	Method	Loss	Dice Scores			Hausdorff Scores			Mean Sensitivity	Mean Specificity
						ET	TC	WT	ET	TC	WT		
Cascaded Methods													
Sun et al. (2021) (Sun et al., 2021)	BraTS 2019	3D	V	3D FCN	CCE	0.76	0.78	0.89	-	-	-	0.80	0.99
	BraTS 2018	3D	V	3D FCN	CCE	0.77	0.79	0.90	-	-	-	0.81	0.99
Havaei et al. (2017) (Havaei et al., 2017)	BraTS 2013	2D	V	Cascaded CNN	SGD	0.73	0.79	0.88	-	-	-	0.82	0.79
Hussain et al. (2017) (Hussain et al., 2017)	BraTS 2013	2D	V	Combined DCNN	Softmax	0.85	0.67	0.80	-	-	-	0.76	0.85
Ranjbarzadeh et al. (2021) (Ranjbarzadeh et al., 2021)	BraTS 2018	3D	V	Cascaded CNN and FCN	CE	0.91	0.87	0.92	-	-	-	0.94	-
Wang et al. (2021) (Wang et al., 2021)	BraTS 2018	3D	V	DFP-ResUNet	CCE	0.84	0.91	0.89	2.19	6.37	5.23	0.89	0.99
	BraTS 2019					0.79	0.85	0.90	3.39	5.98	5.18	0.86	0.99
	BraTS 2019	3D	V	Cascaded U-Net	Dice	0.80	0.86	0.90	3.14	5.43	4.26	-	-
Chen et al. (2019) (Chen et al., 2019a)	BraTS 2018	3D	V	DMF-Net	Dice	0.80	0.84	0.90	3.06	6.44	4.66	-	-
Yang et al. (2020) (Yang et al., 2020)	BraTS 2020	3D	V	DCU-Net	CE	0.83	0.78	0.91	-	-	-	0.85	0.99
Wang et al. (2019) (Wang et al., 2019b)	BraTS 2018	3D	V	ND-Net	Dice	0.72	0.59	0.70	-	-	-	-	-
Zhang et al. (2021) (Zhang et al., 2021a)	BraTS 2020	3D	V	ME-Net	CD	0.70	0.74	0.88	38.6	30.18	6.95	0.79	0.99
Guan et al. (2022) (Guan et al., 2022)	BraTS 2020	3D	V	AGSE-VNet	CD	0.68	0.69	0.85	47.40	31.60	8.44	0.72	0.99
Rehman et al. (2021) (Rehman et al., 2021)	BraTS 2017	3D	V	Brain-SegNet	Custom	0.75	0.79	0.90	-	-	-	-	-
	BraTS 2018					0.77	0.83	0.89					
	BraTS 2019					0.71	0.78	0.87					
Rehman et al. (2020) (Rehman et al., 2020)	BraTS 2017	3D	V	BU-Net	Custom	0.74	0.78	0.89	-	-	-	-	-
	BraTS 2018					0.79	0.84	0.90					
Myronenko et al. (2020) (Myronenko and Hatamizadeh, 2020)	BraTS 2019	3D	V	3D CNN	Dice + Focal	0.80	0.83	0.89	3.921	6.56	5.89	-	-
Cirilio et al. (2021) (Cirillo et al., 2020)	BraTS 2020	3D	V	3D GAN	D+G	0.75	0.79	0.89	36	14.07	6.39	-	-
Jiang et al. (2022) (Jiang et al., 2022)	BraTS 2019	3D	T	Swin-BTS	Dice + CE	0.74± 0.00294	0.79± 0.00234	0.89± 0.0007	0.66± 0.00296	0.70± 0.00216	0.83± 0.00104	-	-
	BraTS 2020		V			0.77± 0.0024	0.80± 0.0079	0.89± 0.0013	0.26	0.15	0.86		
	BraTS 2021		V			0.83± 0.0022	0.84± 0.00227	0.91± 0.078	0.16	0.14	0.03		
	BraTS 2021												
Ensemble Methods													
Kamnitsas et al. (2018) (Kamnitsas et al., 2018)	BraTS 2017	3D	T	EMMA (Unet + FCN)	CE	0.73	0.79	0.90	4.5	6.56	4.23	0.81	-

(continued on next page)

Table 8 (continued)

Papers	Dataset	Dim	Type	Method	Loss	Dice Scores			Hausdorff Scores			Mean Sensitivity	Mean Specificity
						ET	TC	WT	ET	TC	WT		
McKinley et al. (2019) (McKinley et al., 2020)	BraTS 2019	3D	V	Triplanar CNN	BCE	0.77	0.83	0.91	3.92	6.27	4.52	-	-
McKinley et al. (2019) (McKinley et al., 2019)	BraTS 2018	3D	V	D-CNN	Custom	0.79	0.85	0.90	3.55	4.93	4.17	-	-
Feng et al. (2020) (Feng et al., 2020)	BraTS 2018	3D	V	3D UNet	Uniformed	0.79	0.83	0.91	3.97	6.52	3.72	-	-
Ali et al. (2020) (Ali et al., 2020)	BraTS 2019	3D	V	3D CNN + UNet	GDL + Focal	0.75	0.85	0.90	-	-	-	-	-
Rosas-Gonzalez et al. (2021) (Rosas-Gonzalez et al., 2021)	BraTS 2019	3D	V	AE AU-Net	Dice	0.68 ± 0.0032	0.77 ± 0.0008	0.88 ± 0.0008	6.74 ± 13.19	9.49 ± 14.66	9.08 ± 15.16	-	-
Zhang et al. (2021) (Zhang et al., 2021b)	BraTS 2020	3D	CV	3D+ 2D MI-Unet	-	0.82	0.88	0.92	22.94	4.55	4.67	-	-
Krieg et al. (2023) (Guan et al., 2023)	BraTS 2020	3D	V	MVKS-Net (lightweight)	GDL	0.78	0.83	0.89	24.58	10.04	7.62	-	-
				MVKS-Net (Non-lightweight)		0.78	0.83	0.90	24.58	10.04	7.62		
	BraTS 2018	MVKS-Net	0.80	0.83	0.90	2.31	7.63	3.95					
Pre-trained Methods													
Lefkovits et al. (2022) (Lefkovits et al., 2022)	BraTS 2020	3D	V	FCN-ResNet50	Jaccard + Tversky + Dice	0.80	0.84	0.91	-	-	-	-	-
				FCN-ResNet101		0.79	0.85	0.90					
				PSP-ResNet50		0.78	0.84	0.90					
				PSP-ResNet101		0.76	0.84	0.89					
				DeepL-ResNet50		0.80	0.83	0.89					
Ali et al. (2022) (Ali et al., 2022a)	BraTS 2020	3D	V	DeepL-ResNet101	-	0.79	0.85	0.90	-	-	-	-	-
				Unet + VGG19		0.83	0.86	0.90					

Table 9

Open-source projects focused on the segmentation of brain tumors using deep-learning methodologies have been made available. In the present context, the term '3rd Party' pertains to the code that is being re-implemented by an external entity by following the guidelines specified in the corresponding research paper (accessed on 27/10/2023).

Reference	Year	Project Link
(Sun et al., 2021)	2020	https://github.com/JalexDooo/BrainstormTS
(Havaei et al., 2017)	2017	https://github.com/naldeborgh7575/brain_segmentation (3rd Party)
(Wang et al., 2021)	2021	https://github.com/Gaojun211/DFP-ResUnet (3rd party)
(Chen et al., 2019a)	2019	https://github.com/China-LiuXiaopeng/BraTS-DMFNet
(Yang et al., 2020)	2020	https://github.com/pheepa/DCUnet (3rd party)
(Rehman et al., 2020)	2020	https://github.com/nilsec/BUNet (3rd party)
(Rehman et al., 2021)	2021	https://github.com/perronea/BrainSegNet3D (3rd party)
(Cirillo et al., 2020)	2020	https://github.com/mdciri/Vox2Vox
(Jiang et al., 2022)	2022	https://github.com/langwangdezhexue/Swin_BTS
(McKinley et al., 2020)	2020	https://github.com/neuronflow/BraTS-Toolkit/blob/master/README.md
(Feng et al., 2020)	2020	https://github.com/xf4j/brats18
(Ali et al., 2022a)	2022	https://github.com/alinawazT/Brain-Tumor-Segmentation
(Hatamizadeh et al., 2021)	2021	https://github.com/Project-MONAI/research-contributions/tree/main/SwinUNETR/BRATS21
(Roy et al., 2023)	2023	https://github.com/MIC-DKFZ/MedNeXt
(Pinetz et al., 2023)	2023	https://github.com/tpinetz/low-dose-gadolinium-mri-synthesis
(Luu and Park, 2022)	2022	https://github.com/rixez/Brats21_KAIST_MRI_Lab
(Kamnitsas et al., 2016)	2016	https://github.com/deepmedic/deepmedic
(Andermatt et al., 2016)	2016	https://github.com/zubata88/mdgru
(Castillo et al., 2017)	2017	https://github.com/BCV-Uniandes/BCVbrats
(Isensee et al., 2018)	2017	https://github.com/pykao/Modified-3D-UNet-Pytorch (3rd party)
(Pawar et al., 2018)	2017	https://github.com/kamleshpawar17/BratsNet-2017
(Wang et al., 2018)	2018	https://github.com/taigw/brats18_docker
(Isensee et al., 2019)	2019	https://github.com/MIC-DKFZ/nnUNet
(Myronenko, 2019)	2019	https://github.com/IAMsuyogJadhav/3d-mri-brain-tumor-segmentation-using-autoencoder-regularization (3rd party)
(Nuechterlein and Mehta, 2019)	2019	https://github.com/sacmehta/3D-ESPNet
(Zhou et al., 2020a)	2020	https://github.com/chenhong-zhou/OM-Net
(Li et al., 2020)	2020	https://github.com/JohnleeHIT/Brats2019
(Pawar et al., 2020)	2020	https://github.com/kamleshpawar17/Brats19
(Lachinov et al., 2020)	2020	https://github.com/lachinov/brats2019
(Iwasawa et al., 2021)	2021	https://github.com/pfnet-research/label-efficient-brain-tumor-segmentation
(Sundaresan et al., 2021)	2021	https://git.fmrib.ox.ac.uk/vanathi/truenet_tumseg
(Chen et al., 2019a)	2019	https://github.com/China-LiuXiaopeng/BraTS-DMFNet
(Wang, C. Chen et al., 2021)	2021	https://github.com/Rubics-Xuan/TransBTS
(Lyu and Shu, 2021)	2021	https://github.com/shu-hai/two-stage-VAE-Attention-gate-BraTS2020
(Luo et al., 2021)	2020	https://github.com/luozhengrong/HDC-Net

the therapeutic response, and predicting patient results can all benefit from this tumor dissection. Brain tumors can be studied in greater detail as well as treated more specifically for individual patients if they are divided into discrete groups, as is now achievable with the use of genomic sequencing (Westphal and Lamszus, 2011).

6.2.2. Evaluation metrics

The dice coefficient is widely used to assess the similarity between expected and ground truth segmentations. It is defined as follows (Bertels et al., 2019):

$$Dice(X, Y) = \frac{2|X \cap Y|}{|X| + |Y|}$$

Here, x and y are the sets of segmented voxels in the expected and ground truth segmentations, respectively. $X \cap Y$ stands for the point where, x and y meet. The dice coefficient goes from 0 to 1, and a value of 1 means that the predicted segmentation and the ground truth segmentation match perfectly.

Hausdorff distance is a metric for determining the similarity of two sets of points. It is frequently used to assess segmentation accuracy by evaluating the maximum gap between predicted and ground truth segmentations. This is how the Hausdorff distance is defined (Karimi and Salcudean, 2020):

$$d_H(X, Y) = \max \left\{ \sup_{x \in X} \inf_{y \in Y} d(x, Y), \sup_{y \in Y} \inf_{x \in X} d(y, X) \right\}$$

Here, x and y stand for the sets of voxels for predicted and ground truth segmentations, respectively. The segmentation's points x and y are represented by the function $d(x, y)$ and the terms \sup and \inf stand for the

supremum and infimum functions, respectively. The maximum operation's first term determines the most significant separation between each point in x and its closest point in y while the second term determines the largest separation between each point in y and its closest point in x . A smaller Hausdorff distance between x and y denotes a more precise segmentation, and it ranges from 0 to infinity.

Sensitivity: Sensitivity measures the proportion of true positives that are correctly identified, and is given by (Ilhan and Ilhan, 2017):

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

Here, true positives are the number of tumor voxels correctly identified as such, and false negatives are the number of tumor voxels that were incorrectly classified as non-tumor voxels. A higher sensitivity indicates a better ability to detect tumor voxels.

Specificity: Specificity measures the proportion of true negatives that are correctly identified, and is given by (Ilhan and Ilhan, 2017):

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives}$$

Here, true negatives are the number of non-tumor voxels correctly identified as such, and false positives are the number of non-tumor voxels that were incorrectly classified as tumor voxels. A higher specificity indicates a better ability to distinguish between tumor and non-tumor voxels.

6.2.3. Performance Evaluation of cascaded methods

Sun et al (Sun et al., 2021). suggested a method for extracting distinct receptive fields of features using a multi-pathway design and 3D dilated

Table 10

Comparison of recently accessible datasets for segmentation of brain tumors, including the dataset's name, total samples, dimensions, classes, input modalities, type, file category, image shape, and location.

Dataset name	Samples	Dim	Classes	Input modalities	Image type	File Type	Image size	Locations
Figshare (brain tumor dataset, 2023; Deepak and Ameer, 2019; Talukder et al., 2023; Soumik and Hossain, 2020; Polat and Güngen, 2021)	233	2D	3	T1	MRI	mat	-	https://ndownloader.figshare.com/articles/1512427/versions/5
TCGA-GBM (Clark et al., 2013; Rios Velazquez et al., 2015; Kim et al., 2013; Al Mamlook et al., 2023)	500	2D	3	T1, T2	MRI	DICOM, NIFTI	256 × 256 or 512 × 512	https://portal.gdc.cancer.gov/projects/TCGA-GBM
BraTS 2012 (BRATS - SICAS Medical Image Repository, 2023a; Menze et al., 2015; Havaei et al., 2017)	40	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.smir.ch/BRATS/Start2012
BraTs 2013 (BRATS - SICAS Medical Image Repository, 2023a; Menze et al., 2015; Pereira et al., 2016; Havaei et al., 2017; Hussain et al., 2017)	40	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.smir.ch/BRATS/Start2013
BraTs 2014 (BRATS - SICAS Medical Image Repository, 2023b; Sharif et al., 2020; Amin et al., 2018)	274	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.smir.ch/BRATS/Start2014
BraTs 2015 (BRATS - SICAS Medical Image Repository, 2023c; Dong et al., 2017; Kamnitsas et al., 2016)	484	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.smir.ch/BRATS/Start2015
BraTs 2016 (BRATS - SICAS Medical Image Repository, 2023d; Kamnitsas et al., 2016; Li et al., 2019b)	285	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.smir.ch/BRATS/Start2016
BraTs 2017 (MICCAI BraTS, 2017; Rehman et al., 2021, 2020; Kamnitsas et al., 2018)	285	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.med.upenn.edu/sbia/brats2017/data.html
BraTs 2018 (Zhao et al., 2018; Sun et al., 2021; Ranjbarzadeh et al., 2021; Wang et al., 2021; Chen et al., 2019a; Wang et al., 2019b; Rehman et al., 2021, 2020; McKinley et al., 2019; Guan et al., 2023)	285	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.med.upenn.edu/sbia/brats2018/data.html
BraTs 2019 (Multimodal Brain Tumor Segmentation Challenge, 2019; Sun et al., 2021; Wang et al., 2021; Jiang et al., 2020; Rehman et al., 2021; Myronenko and Hatamizadeh, 2020; Jiang et al., 2022; McKinley et al., 2020; Ali et al., 2020)	460	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.med.upenn.edu/cbica/brats-2019/
BraTs 2020 (Multimodal Brain Tumor Segmentation Challenge, 2020; Yang et al., 2020; Zhang et al., 2021a; Guan et al., 2022; Cirillo et al., 2020; Jiang et al., 2022; Zhang et al., 2021b; Guan et al., 2023; Lefkovits et al., 2022; Ali et al., 2022a)	693	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	https://www.med.upenn.edu/cbica/brats2020/data.html
BraTs 2021 (Baid et al., 2021; Jiang et al., 2022)	602	3D	3	T1, T1 contrast, T2, FLAIR	MRI	NIFTI	240 × 240 × 155	http://braintumorsegmentation.org/
ISLES 2015 (ISLES, 2015; Amin et al., 2020; Maier et al., 2016)	28	2D	3	T1, T2, DWI	MRI	DICOM	512 × 512	http://www.isles-challenge.org/ISLES2015/
ISLES 2016–2017 (ISLES, 2016; Hu et al., 2020)	43, 55	2D	3	FLAIR, T1, T1Gd, or T2	MRI	DICOM	512 × 512	http://www.isles-challenge.org/ISLES2016/

convolution. On the BraTS 2018 and 2019 datasets, the model achieved high dice similarity coefficient metrics for the entire, core, and enhancing tumor regions. They found a higher score in the wt class and used categorical cross-entropy as a loss function. The proposed approach by Havaei et al (Havaei et al., 2017). uses a flexible, high-capacity DNN while remaining exceedingly efficient. The research covered many model options required for competitive performance, including a unique CNN architecture that uses both local and global contextual variables at the same time. The primary significance was that this model was perfect for real-time analysis. But the score in the ET class was not so high. To overcome that issue, Hussain et al (Hussain et al., 2017). proposed a combined CNN model. This model is developed by combining many convolutional layers. They trained similarly to the previously used BraTS 2013 dataset. They improved the result for ET class, but the other classes' performances were degraded. Ranjbarzadeh et al (Ranjbarzadeh et al., 2021). proposed a major technique that was lightweight and generated superior outcomes. They integrated the CNN and FCN layers. They presented C-ConvNet/C-CNN for each layer's detailed learning,

where the Distance-Wise Attention (DWA) technique was implemented. The outcomes for both ET and WT classes were above 90%. This cascaded CNN concept was developed by Wang et al (Wang et al., 2021). where dilated convolution technique extracted better features. The authors suggested using a spatial DFP component that consists of numerous parallel dilated convolution layers to extract multiscale characteristics of images. However, these methods were found to be challenging regarding feature extraction. Zhang et al (Zhang et al., 2021a). introduced a model that simplifies feature extraction and significantly enhances model performance. The study's authors also proposed a novel loss function called "Categorical Dice" and implemented a strategy of assigning varying weights to distinct segmented regions concurrently. This approach effectively addressed the issue of voxel imbalance. The primary issue with cascaded CNNs is that they might need help to handle large images well. Since CNNs combine filters across the whole image, high-resolution images can take much memory. Jiang et al (Jiang et al., 2020). devised a cascaded Unet design to solve this problem. Cascading U-Nets are better than cascading CNNs at processing big images because

Table 11

Comparison of recent strategy to handle the modality and missing modality information on various BraTS datasets, MRI modalities, dimensions, modality strategy, evaluation metrics including loss function, dice coefficient (DSC), Hausdorff distance, mean sensitivity, mean specificity, and segmentation targets ("ET – Enhancing tumor; WT – Whole tumor; TC – Tumor core; and '-' Not available').

Papers	Dataset	Dim	Type	Learning Method	Loss	Dice Scores			Hausdorff Scores			Mean Sensitivity	Mean Specificity
						ET	TC	WT	ET	TC	WT		
With Modality Information													
Zhang et al. (2022) (Zhang et al., 2021a)	BraTS 2017	3D	V	Rank + Pair + Fuse	Adv+CC	0.76	0.83	0.9	3.170	6.999	5.155	0.817	-
	BraTS 2018	3D	V	Rank + Pair + Fuse	Adv+CC	0.79	0.84	0.9	3.99	6.37	5	0.867	-
Islam et al. (2021) (Islam et al., 2020)	BraTS 2019	3D	V	Fuse	-	0.7	0.79	0.9	7.05	8.76	6.29	0.82	0.996
Wang et al. (2019) (Wang et al., 2020)	BraTS 2018	2D	-	Fuse	Dice	0.893	+	0.055	-	-	-	-	-
Liu et al. (2020) (Liu et al., 2021)	BraTS 2020	2D	V	Fusion	Dice	0.76	0.8	0.88	21.39	6.68	6.49	-	-
Zhou et al. (2020) (Zhou et al., 2020b)	BraTS 2017	3D	CV	Fusion	-	0.74	0.79	0.87	6.1	7.68	7.54	-	-
Rao et al. (2015) (Rao et al. (2015)	BraTS 2015	2D	-	Rank + Fusion	-	-	-	-	-	-	-	-	-
Fang et al. (2018) (Fang and He, 2018)	BraTS 2018	2D	V	Fuse	-	0.72	0.73	0.86	5.7	9.5	7.5	-	-
Tseng et al. (2018) (Tseng et al., 2017)	BraTS 2015	2D	V	Fuse	CE	0.69	0.68	0.85	-	-	-	0.77	-
Zhang et al. (2020) (Zhang et al., 2020)	BraTS 2018	3D	V	Rank + Fusion	Dice + T-Tset	0.78	0.82	0.9	3.57	9.27	5.73	-	-
Li et al. (2018) (Li and Shen, 2018)	BraTS 2017	2D	V	Pair + Fusion	Focal	0.75	0.71	0.88	-	-	-	-	-
Handling Missing Modalities													
Zhou et al. (2021) (Zhou et al. (2021)	BraTS 2018	3D	V	Fuse with Missing Modality	Dice + MAE	0.71	0.78	0.87	7.1	9.9	6.5	0.83	-
	BraTS 2019	3D	V	Fuse with Missing Modality	Dice + MAE	0.73	0.72	0.87	6.3	9.3	6.7	0.76	-
Yu et al. (2018) (Yu et al. (2018)	BraTS 2015	3D	Sub	Generate Missing Modality	L1	0.68	0.72	-	-	-	-	-	-
Zhou et al. (2020) (Zhou et al. (2020c)	BraTS 2018	3D	CV	Generate Missing Modality	Dice + MAE	0.69	0.79	0.88	-	-	-	-	-
Havaei et al. (2016) (Havaei et al. (2016)	BraTS 2018	3D	V	Generate Missing Modality	L1	0.61	0.55	0.74	-	-	-	-	-
Dorent et al. (2019) (Dorent et al. (2019)	BraTS 2018	3D	V	Generate Missing Modality	L1	0.69	0.79	0.88	-	-	-	-	-
ikYu et al. (2021) (Yu et al. (2021)	BraTS 2019		V	Generate Missing Modality	-	0.78	0.85	0.91	3.69	5.26	4.46	-	-

they work faster. U-Nets work on smaller pieces of an image to process big images with less memory use. Also, the skip links in U-Nets help to keep the image's spatial information, which can help improve the results of segmentation. In multimodal BraTS 2020 analysis, it showed an outstanding performance. Chen et al (Chen et al., 2019a). presented a proficient architecture of a 3D convolutional neural network to segment brain tumors in MRI volumes. The architecture that has been suggested utilizes a 3D multi-fiber unit that incorporates lightweight 3D convolutional networks and 3D dilated convolutions to construct multi-scale feature representations. The experiment's findings indicate that the suggested framework effectively minimizes computational expenses while preserving a notable level of precision for segmenting brain tumors. The authors, Yang et al (Yang et al., 2020)., introduced a novel multiscale efficiency network, which they have named dilated convolution U-Net, to enhance efficiency. The present model undertook pre-processing of the input image at a foundational level. The effectiveness of skip connections in the training networks is improved by adding a dilated convolution residual block. This makes it easier for the network to identify tumor details correctly. The performance of the BraTS 2020 dataset was assessed, revealing excellent results for the ET and WT classes. The ResU-Net model is a fusion of the U-Net architecture and residual connections. Using residual connections facilitates the unobstructed transmission of information from the input to the output of a block of layers. This mechanism simplifies the learning process of the network in capturing information from broader contextual regions. The method employed by Wang et al (Wang et al., 2019b)., resulted in

improving quantitative and qualitative scores. Their applied model worked on residual block level where an extra $1 \times 1 \times 1$ convolution layer is concatenated from input to output. Nevertheless, this model will be helpful if the data post-processing is performed flawlessly. In order to enhance the processing of multiscale images, namely T2, T1-ce, T1, and FLAIR, Zhang et al (Zhang et al., 2021a). were integrated into the encoder section. The encoded input is subsequently transmitted to the decoder layer, where the features of each layer are concatenated. The authors introduced a new network architecture called ME-Net, which primarily consists of down-sampling and up-sampling operations. However, the implementation of this model resulted in an improvement in the WT class outcome while causing a decline in the outcome of the other class. Guan et al (Guan et al., 2022). utilized comparable methodologies and presented an alternative AGSE-VNet architecture. The encoder is equipped with the Squeeze and Excite (SE) module, while the decoder is equipped with the Attention Guide Filter (AG) module. These modules utilize the channel relationship to enhance relevant information and suppress irrelevant information. Additionally, the attention mechanism is employed to guide edge information and eliminate the impact of extraneous factors, such as noise. But in this case, the WT class's performance is better than others. However, there were still drawbacks to using residual block layers, such as incorrect projections for noisy images. To solve this issue, Rehman et al (Rehman et al., 2020). presented the BU-Network, which combined wide context with a residual extended skip. The ET and TC dice outcomes improved when their models were tested on the BraTS 2017 and 2018. Even so, the most

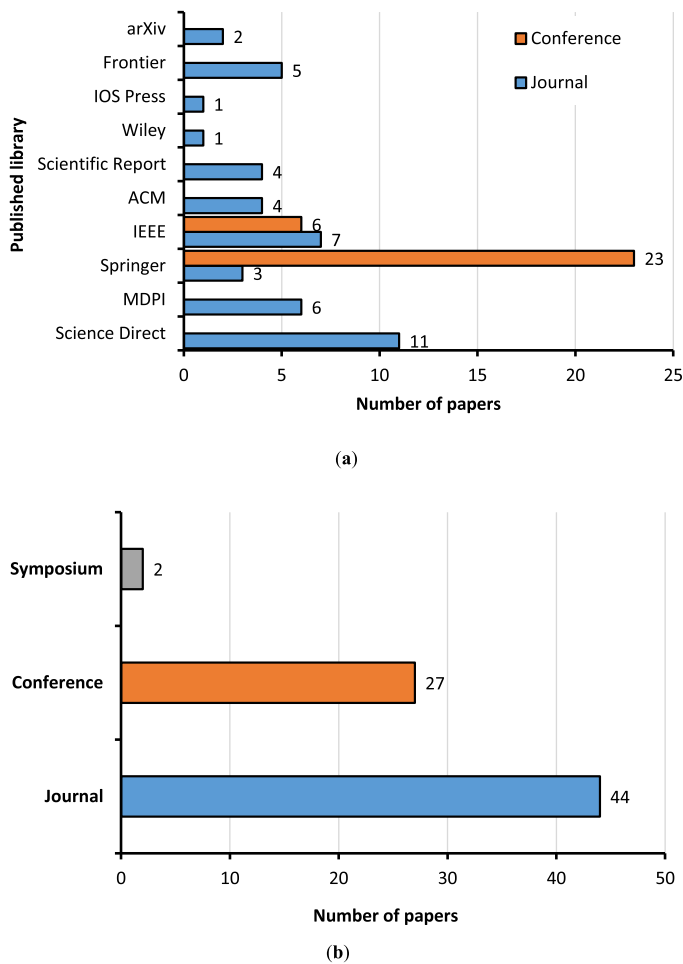


Fig. 6. (a) The distribution of a specific set of papers with publication library, and (b) the distribution of the entire set of selected articles.

significant challenge was that location information and spatial details frequently became lost in the deeper layers. To solve this issue, the BrainSeg-Net (Rehman et al., 2021) model was proposed, which used an encoder-decoder structure. A Feature Enhancer (FE) block was included in the model to collect and distribute intermediate-level features from empty to deep layers. Data from BraTS 2017, 2018, and 2019 were used to test the model's efficacy. Myronenko et al (Myronenko and Hatamizadeh, 2020). suggested a lightweight three-dimensional CNN framework. In the previous study, the computational complexity was lowered, and the segmentation performance was enhanced. The primary factors of significant improvement were optimization and regularization. Dice and Hausdorff's scores improved significantly. Cirillo et al (Cirillo et al., 2020). proposed a generative associate network to segment multiclass tumors, but the Hausdorff score needed to be improved, and ET and TC dice scores decreased. Jiang et al (Jiang et al., 2022). recently suggested a transformer-based technique for multimodal segmentation comparable with the state of the art. Because of their self-attention mechanism, transformers can work adequately on semantically encoded data, making them suited for challenging prediction tasks such as 3D medical image segmentation. The dice and cross-entropy loss functions were utilized. Their model found a balanced result in the BraTS 2021 dataset. The performance scores on the cascaded model are briefly presented in Table 8.

Cascaded models have shown proficiency in multi-scale feature representation, which is crucial for identifying the nuances of brain tumors in MRI imaging (Havaei et al., 2017; Sun et al., 2021; Yang et al., 2020). To achieve this, intricate architectures such as parallel dilated

convolutions and multi-fiber units capture features at various scales, improving segmentation accuracy (Myronenko and Hatamizadeh, 2020; Hussain et al., 2017; Ranjbarzadeh et al., 2021; Wang et al., 2021; Zhang et al., 2021a; Chen et al., 2019a). Additionally, these models are efficient, with designs such as the dilated convolution U-Net and transformer-based network increasing processing speed, which is a critical factor in time-sensitive clinical environments (Jiang et al., 2022, 2020). Furthermore, some models have demonstrated significant advancements in segmenting specific tumor regions, indicating their enhanced ability to acquire knowledge and adapt to subtle data. Integrating local and global contextual information enhances the analytical capabilities of these models, allowing for a more comprehensive examination of tumors (Wang et al., 2019b; Guan et al., 2022; Rehman et al., 2020, 2021; Cirillo et al., 2020). These models effectively handle the hierarchical characteristics of tumors by utilizing inter-slice features and managing memory burden more efficiently than full 3D CNNs (Chen et al., 2019a). Their exceptional performance in challenging tasks, such as BraTS, demonstrates their effectiveness in clinical evaluation and treatment strategy development.

Despite their effectiveness, these models have some significant limitations. High-resolution image processing requires much computational power, which can be problematic in low-resource environments (Jiang et al., 2022, 2020; Myronenko and Hatamizadeh, 2020; Sun et al., 2021; Hussain et al., 2017; Ranjbarzadeh et al., 2021; Wang et al., 2021; Yang et al., 2020). Achieving a balance between performance across different tumor classes is also a challenge, as improvements in the segmentation of one class may result in a decline in performance for another (Zhang et al., 2021a; Chen et al., 2019a). Processing large images also requires much memory, partially alleviated by cascaded U-Nets. When training data is limited, these complex models may result in overfitting. Additionally, deeper network layers may result in the loss of critical spatial information, impairing segmentation accuracy. These limitations highlight the need for careful model development and optimization methodologies to ensure that the benefits are maximized while the constraints are minimized.

6.2.4. Performance evaluation on ensemble methods

According to the performance Table 8, multiclass balance performance is achieved through ensemble technique, notably at ET class result. To improve the lower-class score, several researchers used ensembling multiple models and compared the results. Kamnitsas et al (Kamnitsas et al., 2018). introduced the EMMA approach in 2018, which implies ensembles of different models and architectures. They proposed the deepmedic ensemble model, which they created by combining FCN and U-Net. FCN combines regular and low-resolution routes to create an efficient lesion. Both models were trained independently. The BraTS 2017 validation set was used to forecast the ensemble results. However, the FCN model had a limitation for segmentation due to its inability to capture fine-grained spatial details due to down-sampling operations, which resulted in a loss of resolution. McKinley et al (McKinley et al., 2019). developed a convolutional strategy that uses dilated convolutions in densely connected blocks within a shallow U-net structure that uses downsampling, up sampling, and skip connections. The researchers evaluated the model's performance using the BraTS 2018 dataset. They also developed an attention technique for locally focusing CNNs and advocated, for instance normalization rather than batch normalization (McKinley et al., 2020). A previously disclosed BCE loss function was used to train the networks. The BraTS 2019 dataset was employed to test the results. In 2020, Feng et al (Feng et al., 2020). proposed an efficient but lightweight end-to-end model. The authors created an adaptation-based 3D Unet model to address the primary issue with multimodal MRI images, like class imbalance. The random errors of individual models were reduced by using an ensemble of models trained with distinct hyper parameters, leading to better overall performance. On the BraTS 2018 LGG samples, ensemble models performed exceptionally well. Ali et al (Ali et al., 2020). also proposed an ensemble model based on CNN.

Generalized soft dice loss with focal loss was evaluated on the BraTS 2019 dataset. Rosas-Gonzalez et al (Rosas-Gonzalez et al., 2021). proposed a modified ensemble UNet model in which 3D and 2.5D convolutional methods were maintained. For extracting low-level features, the 2.5D method yielded excellent results, while the 3D model was utilized for concatenation. In order to strike a balance between improving multi-scale and 3D contextual information extraction and maintaining low memory usage, the Asymmetric Ensemble of Asymmetric U-Net (AE AU-Net) was devised. Therefore, the ET class performed better on the 2019 BraTS evaluation set. Cross-validation is a technique used to evaluate how effectively a model generalizes to new, untested data. Zhang et al (Zhang et al., 2021b). employed cross-validation for the UNet model and maintained three UNets with distinct inputs. Before the segmented output, each image was processed. Using the most recent BraTS 2020 data, they achieved the highest feasible dice scores of 0.82 in the ET class, 0.88 in the TC class, and 0.92 in the WT class. The existing CNN models' primary shortcoming was their use of a multi-branch structure with independently chosen convolution kernel sizes to accommodate a range of tumor sizes. The outcome was unreliable if calculated using kernels of varying sizes. Multilevel ensembling with shared kernels and the dilating convolution method were offered as potential solutions to the problem. Krieg et al (Guan et al., 2023). proposed a hierarchical multi-view convolution approach, which divides the regular 3D convolution into axial, coronal, and sagittal views to supply complementary-view characteristics. Their suggested lightweight and non-lightweight models performed almost the same, but the lightweight model took less time to process.

Ensemble methods, including integrating multiple UNet models, present unique benefits and certain obstacles in segmentation tasks. Their primary advantages are their precision and resilience (Kamnitsas et al., 2018; McKinley et al., 2019, 2020). Securing accurate medical diagnosis requires segmentation results that are more precise and generalizable; this is achieved through the integration of various models and architectures (Feng et al., 2020; Ali et al., 2020). Additionally, they provide pixel-level accuracy, which enables a comprehensive examination that can be especially advantageous when the dataset is small. They aid medical professionals in comprehending concepts through visual representations (Rosas-Gonzalez et al., 2021; Zhang et al., 2021b; Guan et al., 2023).

Nevertheless, the implementation and administration of these models are complicated, thereby presenting obstacles. They might necessitate substantial computational resources, which can pose a challenge, particularly in environments with constrained infrastructure (Kamnitsas et al., 2018; McKinley et al., 2019, 2020; Feng et al., 2020; Ali et al., 2020). Moreover, although ensemble methods may improve performance for certain classes of tumors, this improvement may not be uniform across all tumor varieties and sizes (McKinley et al., 2020; Feng et al., 2020; Guan et al., 2023). Additionally, processing time may be prolonged due to multiple models operating in concert. Despite these obstacles, the implementation of ensemble methods providing a harmonious equilibrium between enhanced performance and efficient utilization of resources (McKinley et al., 2020; Feng et al., 2020; Zhang et al., 2021b; Guan et al., 2023). Ongoing efforts are made to refine these methods as research advances to minimize their intricacy and resource demands while preserving or potentially enhancing their precision and applicability.

6.2.5. Performance evaluation on pre-trained methods

Since the ET class only represents a tiny percentage of the tumor and it might be challenging to discern its region from normal brain tissue, its performance in the segmentation of brain tumors is not always high. Some researchers explored sophisticated methodologies to solve the problem. Pretrained models can enhance the effectiveness of ET class segmentation by taking advantage of the extensive training data. Lefkovits et al (Lefkovits et al., 2022). suggested using several deep learning methods available through the AWS SageMaker framework. They modified and improved several CNN designs utilizing the backbone

network. To establish the optimal parameters for the models, the experiments were assessed and analyzed. In the segmentation, the background of healthy tissue, the whole tumor, the tumor core, and the enhanced tumor were separated. In order to further enhance the given designs, they also proposed a random search for parameter optimization. Then, they calculated the ensemble performance. Resnet50 with FCN model showed the highest dice score for multiple class. Ali et al (Ali et al., 2022a). published an effective convolutional neural network model for segmenting brain tumors called an attention-based neural network. The authors employed a strategy that involved utilizing a pre-trained VGG19 network as the encoder component of the UNET. The decoder parts were positioned adjacent to the encoder and included an attention gate to minimize noise during segmentation, as well as a denoising mechanism to prevent overfitting. The authors evaluated their algorithm using the BraTS'20 dataset, which consisted of four distinct MRI modalities and a target mask file. The results of the proposed method indicate that it was successful in enhancing the dice similarity coefficient for the core and whole tumors, achieving values of 0.86 and 0.90, respectively. Additionally, the method achieved a dice similarity coefficient of 0.83 for the enhanced tumors. The performance scores on pre-trained methods are briefly presented in Table 8.

The use of pre-trained models utilized a vast amount of training data and the latest deep learning architectures shared within the community, models such as ResNet50 and VGG19 offer significant advantages (Lefkovits et al., 2022; Ali et al., 2022a). One of the most challenging tasks in this field is to distinguish small tumor regions from normal brain tissue, and these models are constructive for this. They enable classification without manual feature extraction and are particularly effective for the less common and hard-to-distinguish ET class. Moreover, these models can mitigate overfitting issues common with smaller datasets, as they bring in learned patterns from extensive prior training. However, there are challenges, too. The dependency on large pre-existing datasets for initial training might introduce biases or irrelevant feature recognition when applied to specific medical imaging tasks specifically on early and accurate diagnosis (Ali et al., 2022a). The complexities of deep learning models also demand substantial computational resources, which can be a bottleneck in specific clinical settings. Balancing these advantages and disadvantages is crucial for advancing computer-assisted diagnosis in neuro-oncology and improving patient outcomes through precise and timely medical interventions.

Currently, no commercial software products are available for clinical examination of brain tumors. The available open source project links have been mentioned at Table 9.

6.2.6. Summary

Performance in brain tumor segmentation is influenced by diverse characteristics and techniques. After analyzing the performance of various models in Table 8, several key observations have been made.

1. High-capacity, flexible DNNs with distinctive CNN architectures enable real-time analysis and improved flexibility. Cascaded CNN and FCN layers have achieved high dice similarity coefficients on distinct tumor classes while keeping the model lightweight. Multi-pathway configurations and dilated convolution U-Nets extract features and preprocess input images, while cascaded U-Nets process large images and residual connections to improve feature learning.
2. The process of downsampling can limit the capturing of detailed information. However, convolutional strategies that include attention mechanisms, and instance normalization have enhanced the performance. The implementation of lightweight and efficient 3D UNet models has effectively resolved concerns related to class imbalance. Additionally, CNN-based ensemble models utilizing soft dice loss have shown improved results but the model's computational cost being high. Using hierarchical multiview convolutions techniques can improve complementary-view characteristics. By

integrating these methods, the precision, clarity, and resilience of tumor regions can be improved.

3. Optimizing the efficacy of tumor, especially for the challenging ET class, requires implementing efficient strategies. Pretrained models utilize substantial training data to extract most features by optimizing parameters and exhibiting distinct demarcation of different regions. Random parameter searches can further refine the models. Attention-based neural networks prevent overfitting issue and minimize noise. But those pre-trained methodologies increase the model weight and make it difficult to use in clinical applications.

6.3. Standard datasets used for identification of spot tumors

Publicly accessible to privately obtained datasets are included in this research. Machine learning techniques for medical image interpretation rely heavily on datasets for training and testing. The size, complexity, modality, and image quality of a dataset can have a considerable effect on the performance and generalizability of the algorithms. Researchers can find the best techniques for future research by examining numerous datasets and comparing the strengths and weaknesses of different approaches and datasets. Datasets can also help with findings' repeatability and benchmarking. Researchers may see how well their methods perform on publicly available datasets, and other researchers can replicate their studies and assess them against alternative approaches. This could improve our understanding of the state-of-the-art in federated learning and brain tumor segmentation, as well as accelerate the creation of novel techniques and algorithms. Finally, talking about datasets can help find research holes and open doors. Researchers can pinpoint the shortcomings of present methods and suggest novel avenues for exploration by examining existing datasets. Benchmark datasets have been used extensively in the chosen studies to figure out how to diagnose brain tumors. The following are some of the most common benchmark data sets. This review paper focuses on BraTS, which is a widely accepted benchmark dataset specifically designed for evaluating algorithms and models for brain tumor segmentation in magnetic resonance imaging (MRI) scans. This dataset contains high-quality images and a variety of tumor types. Normal dose MRI provides the highest image quality and is better suited for detailed anatomical and pathological assessment of tumors. Low dose CT scans produce images with less detail, potentially missing critical diagnoses due to reduced radiation, while low dose MRI can have a lower signal-to-noise ratio, reduced image homogeneity, and impaired detection of calcifications (Ma et al., 2011). This review paper focuses on the most used BraTS dataset, which contains normal-dose MRI samples, and the maximum number of researchers who worked on this specific dataset. These attributes establish MRI as the most appropriate modality for precise and detailed tumor delineation in clinical practice and research. In Table 10, the dataset details are presented with the number of total samples, image size with modality information and the downloadable source link.

6.3.1. Figshare dataset

Figshare is an open directory (brain tumor dataset, 2023). It consists of 3064 T1-weighted enhanced magnetic resonance imaging (MRI) observations. The data from 233 patients was collected and analyzed from healthcare facilities and medical centers. The dataset includes three forms of brain tumors: gliomas, pituitary tumors, and meningiomas. Sagittal, axial, and coronal perspectives are used to capture datasets. There are 1426 glioma specimens, 930 pituitary specimens, and 708 meningioma specimens. The images have a resolution of 512×512 and are stored in the ".mat" format. In a binary mask image, each tumor border, its corresponding reference locations, and the ground truth are presented.

6.3.2. TCGA-GBM dataset

Glioblastoma multiforme is the most common and deadly primary brain tumor, and the TCGA-GBM dataset provides a publicly available

database of molecular and clinical data for this disease. The National Cancer Institute's dataset included the medical records of more than 500 GBM patients (Clark et al., 2013). Imaging data, genetic data, and clinical data are all included in the dataset. MRI scans of various sorts, including T1- and T2-weighted images taken before and after surgery, make up the imaging data. Clinical information consists of patient characteristics, tumor characteristics, and therapy details. Brain tumor diagnostic, therapy, and prognosis studies, as well as machine learning algorithm development for brain tumor segmentation and classification, have all made heavy use of the TCGA-GBM dataset. The availability of such a vast and varied dataset to develop and test new approaches and algorithms has dramatically aided the progress of research in this area. The dataset is available for download in several forms (including DICOM, NIFTI, and CSV), and it also includes documentation and metadata to aid with data analysis.

6.3.3. BraTS 2012 datasets

The BRATS 2012 dataset is accessible to the public and comprises MRI scans of the brain that have been accurately segmented to identify gliomas. The dataset was generated for the Brain Tumor Image Segmentation (BRATS) Challenge 2012 (BRATS - SICAS Medical Image Repository, 2023a). It comprises 40 cases, of which 30 are associated with high-grade gliomas, and the remaining 10 are associated with low-grade gliomas. Domain experts have meticulously annotated all of the cases in the dataset. Various MRI scan methods were used to capture the pictures; these included T1-weighted, T2-weighted, and contrast-enhanced T1-weighted scans. The dataset encompasses data on patient age, gender, and tumor location. Reports and software that make it easier to manipulate and evaluate data come with the dataset. Furthermore, it is publicly accessible for download. The data is stored in NIFTI format, a widely used format for medical image analysis. The dataset comprises the original image data along with ground truth segmentation labels. Researchers use this dataset to test and develop novel segmentation algorithms, assess their performance compared to current methods, and look into the relationship between tumor grades and imaging variables.

6.3.4. BraTS 2013 dataset

The 2013 BRATS dataset is freely accessible to the public. The dataset contains MRI images of the brain of 30 patients with glioblastoma multiforme (GBM) and 10 patients with lower-grade gliomas, such as T1-weighted, T1-weighted contrast, T2-weighted, and FLAIR images (BRATS - SICAS Medical Image Repository, 2023a). These pictures are helpful for algorithm development and validation since they are labeled with ground truth segmentations of the tumor, including the necrotic core, the enhancing tumor, and the peritumoral edema. Images taken before and after surgery are also included in the collection to help analyze the tumor's response to therapy. The segmentation, classification, and prognosis of brain tumors have all been extensively studied using the BRATS 2013 dataset.

6.3.5. BraTS 2014 and 2015 dataset

They are both freely accessible datasets created to test automatic segmentation techniques in brain tumors. 274 brain MRI scans from the BraTs 2014 dataset, including 220 cases of high-grade and 54 cases of low-grade gliomas, are included (BRATS - SICAS Medical Image Repository, 2023b). The 274 high-grade glioma patients in the BRATS 2015 dataset had a total of 484 multi-modal MRI scans (BRATS - SICAS Medical Image Repository, 2023c). T1-weighted, T1-weighted contrast-enhanced, T2-weighted, and fluid-attenuated inversion recovery (FLAIR) sequences were among the MRI modalities used to acquire the pictures. Each scan was manually divided into four sections: the core of the tumor that was not enhancing, the tumor that was enhancing, the edema, and the necrosis. Additionally, the dataset contains clinical information such as age, gender, and survival period. NIFTI is the file format.

6.3.6. BraTS 2016 and 2017 dataset

The 2016 BRATS (Multimodal Brain Tumor Segmentation Challenge) dataset comprises 285 cases, 210 high-grade gliomas, and 75 low-grade gliomas, and uses 4 MRI modalities: T1, T1-contrast enhanced, T2, and FLAIR. $240 \times 240 \times 155$ voxels of spatial resolution are provided for the images in NIFTI format (BRATS - SICAS Medical Image Repository, 2023d). The dataset also has binary masks for segmenting tumors and edema. The same 4 MRI modalities—T1, T1-contrast enhanced, T2, and FLAIR—were used in 285 cases in the BRATS 2017 dataset, including 210 high-grade and 75 low-grade gliomas. $240 \times 240 \times 155$ voxels of spatial resolution are provided for the images in NIFTI format (MICCAI BraTS, 2017). The dataset also contains segmentation labels for the enhancing tumor, the entire tumor (which includes the enhancing tumor, non-enhancing tumor, and edema), and the tumor core (which includes the enhancing and non-enhancing tumor). Patient survival information is also included in the dataset.

6.3.7. BraTS 2018 and 2019 dataset

The dataset of BraTS 2018 comprises of a total of 285 cases of high-grade glioma (HGG) and 66 cases of low-grade glioma (LGG) (Zhao et al., 2018). The dataset known as BRATS 2019 comprises a total of 460 cases, of which 335 are classified as HGG and 125 as LGG (Multimodal Brain Tumor Segmentation Challenge, 2019). The acquisition of these cases utilized identical MRI sequences as the dataset from the previous year. Data acquisition was performed utilizing various MRI sequences, comprising T1-weighted, T1-weighted with gadolinium contrast enhancement, T2-weighted, and fluid-attenuated inversion recovery (FLAIR). The voxel size of the images was standardized to 1 mm^3 in an isotropic manner, while the dimensions of the images were $240 \times 240 \times 155$. The dataset incorporates segmentation masks for three distinct sub-regions of the tumor, namely the enhancing tumor, non-enhancing tumor, and edema, in addition to a comprehensive tumor region. The information is obtainable in the NIFTI format.

6.3.8. BraTS 2020 and 2021 dataset

Brain tumor MRI images (gliomas and meningiomas) are the focus of both the BraTS 2020 and 2021 datasets. Various modalities, including T1, T1-contrast, T2, and FLAIR, are present in the photos, which were gathered from numerous institutions. There are 484 samples of high-grade glioma (HGG) and 209 samples of low-grade glioma (LGG) in the 2020 dataset (Multimodal Brain Tumor Segmentation Challenge, 2020), and 406 HGG and 196 LGG samples in the 2021 dataset (Baid et al., 2021), respectively. Each image contains $240 \times 240 \times 155$ pixels. Accurate segmentation maps are included with the given photos, revealing the tumor core, the enhancing tumor, and the entire tumor. Furthermore, the datasets comprise clinical data encompassing patient age and tumor grade. The datasets, as mentioned earlier, have been utilized for diverse research objectives, such as creating machine-learning models for the segmentation and diagnosis of brain tumors.

6.3.9. ISLES 2015 dataset

ISLES 2015 is a publicly accessible dataset to assess algorithms for segmenting ischemic stroke lesions. There are 28 instances in the dataset, and each case consists of MRI images obtained at various intervals following the commencement of the stroke. The images have a resolution of 256 or 512×512 pixels and are saved in the DICOM format. There are 20 photos in the training set and 8 in the testing set, both of which have been identified as such. T1-weighted, T2-weighted, and diffusion-weighted imaging (DWI) scans are all represented in the collection. The dataset includes a collection of expert segmentations of the ischemic lesion on the DWI scan for each case, which can be utilized as the benchmark for assessment (ISLES, 2015).

6.3.10. ISLES 2016 and 2017 dataset

The ISLES 2016 dataset consists of 43 3D MRI scans with 28 training examples and 15 test cases from 28 organizations. The resolutions and

fields of view of the photos differ because different procedures and equipment were used to capture them. Two expert radiologists provided the ground truth labels for the lesions, and a decision-making consensus was reached. The ISLES 2017 dataset includes 55 cases analyzed using one of four distinct types of magnetic resonance imaging (MRI) modalities: FLAIR, T1, T1Gd, or T2. Every imaging modality has the exact picture resolution, which is $240 \times 240 \times 155$ pixels, and the voxel size is $1 \times 1 \times 1 \text{ mm}^3$ (ISLES, 2016).

6.3.11. BRAINIX dataset

More kinds of datasets can be used to make research more accurate. However, this BRAINIX dataset is only available to some. A particular DICOM library set maintains and manages this dataset privately. This dataset can only be accessed by those who have been granted unique permission (OsiriX DICOM, 2023).

6.4. Impact on multi-modality information

Multimodality information is essential for brain tumor segmentation because it makes it possible to segment the tumor more completely and accurately. Brain tumors can show different features in different imaging methods, such as T1-weighted, T2-weighted, contrast-enhanced T1-weighted, and FLAIR MRI sequences. Each method gives different information about the location, shape, size, intensity, and enhancement patterns of the tumor growth. After reading many research papers, we found that most researchers used the BraTS challenge datasets. With multi-multimodality data, the segmentation score improves and becomes more accurate. As a result, if the collected modality information is valid, the model with inferior performance can be ranked higher (Islam et al., 2021; Zhou et al., 2020a; Andrade-Miranda et al., 2023; Peng et al., 2022; Zhou et al., 2023b; Taghanaki et al., 2018; Liu et al., 2023; Njeh et al., 2015). This section is classified into two groups: using multi-modality information and missing modality information. The performance metrics after handling with complete modality and missing modality are briefly demonstrated in Table 11.

6.4.1. Utilizing multimodality information

Zhang et al (Zhang et al., 2021a). used multimodal MRI data to develop a new cross-modality deep feature learning method for separating tumors. Cross-modality feature transition (CMFT) and cross-modality feature fusion (CMFF) were the two main learning methods in this framework. To make up for the small amount of data, the CMFT process focused on finding rich patterns in data from different sources. It involved learning how to represent features by moving information across different data types. The goal of the CMFF method was to bring together information from different types of data. A cross-modality at different types of A and B modalities feature transition and feature fusion is presented in Fig. 7. This made it easy to find patterns in the collected data for each modality.

6.4.1.1. Ranking the modalities. For each modality, a comparison function is used to determine the relative significance or relevance of the modality. The first study on learning to rank was done by (Rao et al., 2015). This research laid the groundwork for learning to rank. The work converted each modality into a singular Network (CNN). Each feature was linked with a different modality.

In another study (Zhang et al., 2021a), a similar method was followed, and here, two different networks were used to process the model. The settings for each network were changed because of the different control losses. Using the BraTS 2015 dataset, the study looked at how different ways of embedding were used to pull out behaviors. The second method will only work if there are at most one or two modes. However, when only one modality is present, the outcomes are less excellent than a model trained only on that modality.

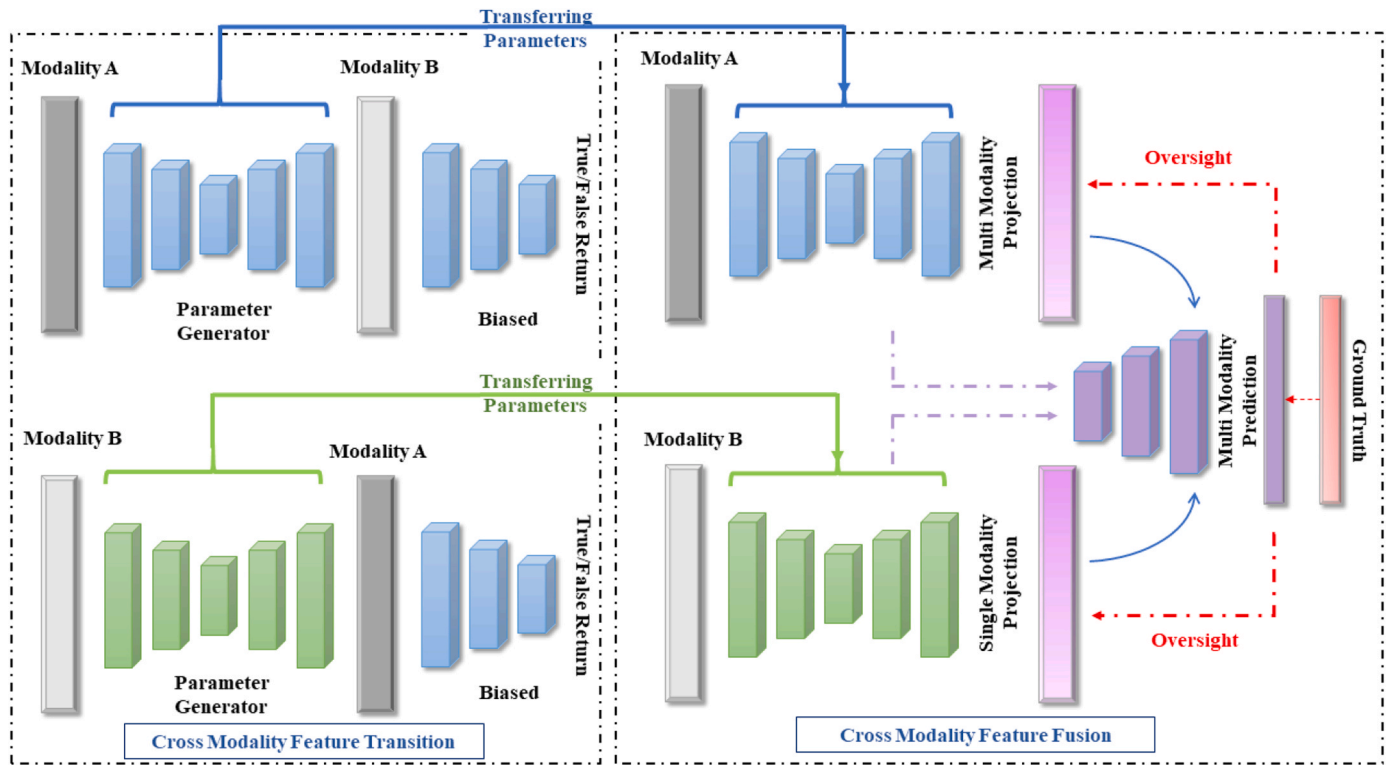


Fig. 7. The cross-modality feature learning architecture is presented for both cross-modality feature transition and cross-modality feature fusion.

6.4.1.2. *Pairwise multimodal task.* The best way to get good results is to use modality-modality pairwise mixing. In (Li and Shen, 2018), it is the first attempt to build a model that shows how different forms interact with each other. The authors paired every pair of modes and then sent all possible combinations of pairings to the secondary network. The cross-modal attention module and the modal coupling module serve to strengthen the relationship between modalities (Zhang et al., 2020). The goal is to expedite the process of incorporating and shifting characteristics across different modalities in order to acquire additional data and improve overall efficacy.

6.4.1.3. *Fusion mechanism of modalities.* Modern multimodality techniques have progressed significantly since the days of ranking and coupling modalities. Modality fusion is the process of combining different traits from different modalities in order to get more accurate segmentation. Early fusion is a relatively simple process that usually involves combining or incorporating features from different modes by stringing them together or adding them. Based on how they use the encoder-decoder structure, multi-modal feature fusion methods can be put into four different groups. Fig. 8 shows different types of fusion strategies indicating the fusion places. After the first few layers of each

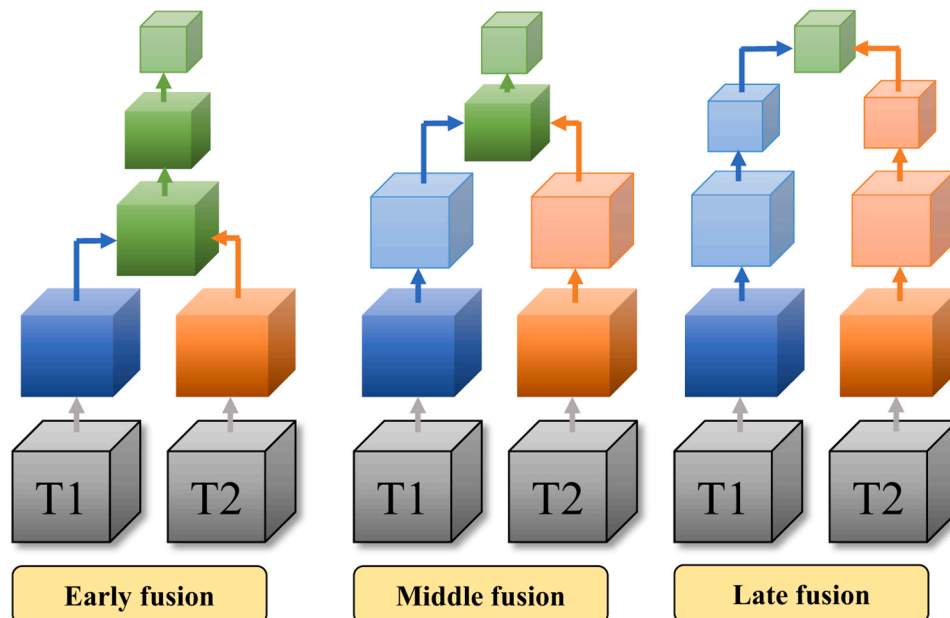


Fig. 8. Different points of fusion. The sequence of early, middle, and late fusion points is presented in a left-to-right orientation (Islam et al., 2020).

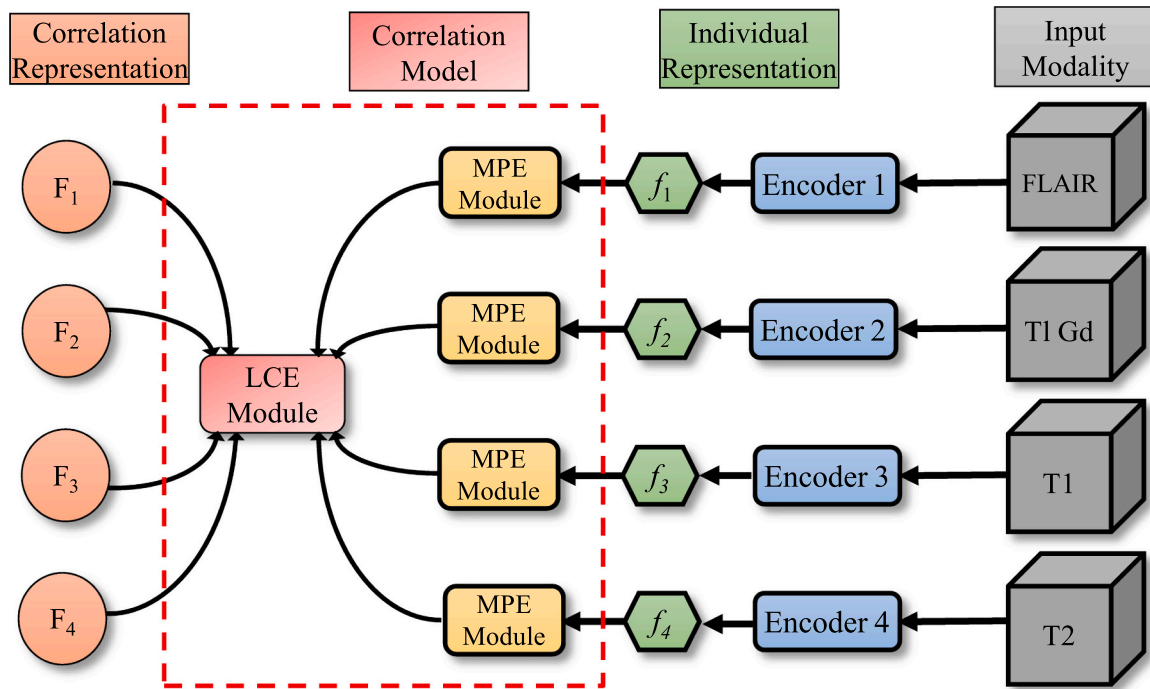


Fig. 9. The representation shows how to handle missing modalities utilizing correlational modeling (Zhou et al., 2021).

CNN, in the early form of the convolutional neural networks, those are combined. On the other hand, the CNNs in the later form are combined in the layers after that. How "early" and "late" are used depends on the Design (Aygün et al., 2018).

The fusion of information from various modalities occurs at the initial stages of the learning pipeline in early fusion. Commonly, the process entailed merging or arranging the feature representations derived from individual modalities, followed by feeding them into a unified single stream of network (Isensee et al., 2021). In (Rao et al., 2015), the authors employed four networks to extract modality-aware features and then combined them.

In (Orbes-Arteaga et al., 2018), a combination of T1 and Flair features was sent to the downstream network to segment the entire tumor. In (Zhang et al., 2020), feature extraction is performed while taking modalities into account, and the data is then passed on to a downstream network for training.

In the middle fusion approach, the merging of phases at the network's input was avoided by employing a middle-fusion strategy. This strategy involves the independent processing of different modalities in their respective encoders while utilizing a shared decoder for feature fusion and final segmentation. This methodology had been previously proposed and documented in (Chen et al., 2019b).

The late fusion approach involved the independent processing of each modality, with subsequent fusion of the representations or predictions from each modality at a later stage (Sun et al., 2017). The integration of multiple modalities took place at the level of decision-making through the amalgamation of the outcomes derived from distinct modality models. The integration of multiple modalities was achieved through late fusion, which involved concatenating or merging the extracted features at the feature level.

6.4.1.4. Attention mechanisms. With this method, the model can focus on the most critical modalities based on the tasks and data available. In recent years, many studies have used attention strategies to reinforce the acquired skills. A spatial and channel attention-based fusion module was employed in (Islam et al., 2020; Zhou et al., 2020b; Liu et al., 2021; Wang et al., 2020). In order to achieve precise segmentation, the

suggested attention mechanism emphasizes relevant traits while suppressing irrelevant ones.

6.4.2. Handling missing modalities

In multimodal learning, "handling absent or unavailable modalities" means figuring out what to do when one or more modalities are not there or cannot be used in a particular situation. In actual application scenarios, however, it takes much work to acquire complete and high-quality multi-modality datasets. Two main strategies can be implemented to handle this problem, such as synthesizing and learning modality invariant feature.

6.4.2.1. Synthesizing missing modalities. It is possible to train a generative model to synthesize the absent modalities, followed by the execution of multi-modal segmentation. In reference to (Yu et al., 2018), the authors created the sole extant modal T1 and employed generative adversarial networks to produce the absent modalities. The study conducted by the authors in reference (van Tulder and de Bruijne, 2015) demonstrated that the utilization of a synthesized modality results in an enhancement of the precision of brain tumor detection.

6.4.2.2. Learning modality invariant feature. The second approach involves acquiring a feature space invariant to modality, which captures the multi-modal information during the training phase and enables the utilization of all conceivable modal combinations during inference. HeMIS was proposed by Havaei et al (Havaei et al., 2016), which involved the training of distinct feature extractors for each modality. Dorent et al (Dorent et al., 2019), developed a novel approach called U-HVED, which HeMIS influenced. The authors incorporated skip-connections regarding intermediate layers as a feature map before each down-sampling step. The network exhibited superior performance to HeMIS when evaluated on the BraTS 2018 dataset.

In reference to sources (Zhou et al., 2020c) and (Zhou et al., 2021), the authors acquired knowledge of the implicit correlation between modalities and conducted a thorough analysis of all potential absent scenarios. The researchers utilized the pre-existing T1 modality as an input to produce the Flair modality. The supplementary Flair data is

generated and transmitted alongside the primary T1 data to the subsequent segmentation network. This methodology acquired knowledge of the implicit correlation among modalities and scrutinized all conceivable absent situations (Zhou et al., 2021). Fig. 9 represents the overall working approach to handle the missing modality.

6.4.3. Summary

Upon examining the effects of multi-modality information and the comparative performance from Table 11, a few key observations have been made.

1. Task-modality modelling enables a network to improve its capacity to select the most relevant and supportive modality for accurate segmentation by acquiring the ability to rank modalities. In most research studies, the main objective is to model the implicit ranking of modalities as the network receives modality-aware features.
2. Integrating multi-modality data can enhance the expressive capacity and generalizability of features. However, the existing fusion tech-

Require: Number of Steps = H, Step size = α Learning Rate = η ,

Local Minibatch size = B, Client Data = D

```

1: function ClientUpdate(i,0)           // k no. of Clients
2:   Initialize  $\varphi_{i,0} \leftarrow \varphi$ 
3:   for t = 0, 1, 2, ..., T - 1 do
4:     Sample a training batch from client data D
5:     Compute Gradient
6:     Update Local Gradient  $\varphi_{i,t} = \varphi_{i,t-1} - \alpha \nabla_{\varphi} f_i(\varphi_{i,t-1})$ 
7:   end for
8:   Return  $\varphi_{i,t}$  and E to Server           // Server Collects the Updates
9: end function

```

niques have their strengths and weaknesses. Additional fusion strategies do not introduce extra parameters but may require more physically manifesting characteristics. On the other hand, using a compact network with an attention module can fine-tune feature expression, but it comes with added parameters and increased computational overhead.

3. In clinical imaging, it is expected to overlook situations where specific modalities are not available. Previous research has focused on

Require: Number of rounds

```

1: function Aggregating
2:   Initialize  $\theta_0$ 
3:   for each round t = 1, 2, ... do
4:     The server randomly selects a set  $S_t$  of N clients and
       broadcasts the global parameter to them
5:     for each client  $k \leftarrow 1 \cdots K$  do           //Running in parallel
6:       Sending  $\varphi_i \leftarrow$  ClientUpdate(i,  $\theta_{t-1}$ )
7:       Update  $\theta_i$ 
8:     end for
9:      $\theta_t \leftarrow \frac{1}{m} \sum_{i \in S_t} \theta_i$            // Server averaging
10:  end for
11: end function

```

generating missing modalities based on existing modality data. However, it is essential to note that the quality of the generated modalities largely depends on the quality of the available modality data.

6.5. Impact of privacy and performance on federated learning

Medical data privacy regulations often make it hard to gather and share patient data in a central data center. The Federated Stochastic Gradient Descent (FedSGD) technique is a straightforward translation of the traditional algorithm into a federated learning framework. This requires the implementation of a client-side model training process and a server-side model aggregation procedure (Li et al., 2019a). Fig. 10 represents the architecture of the learning strategy among the federated server and client-server area.

At first, it is suggested that there are K clients, each of which is linked and has a fixed local dataset and enough computing power to run mini-batch SGD updates. All clients have the same design and loss function for their neural networks (Song et al., 2022). Algorithm 1 can be used to do the work described above.

Algorithm 1. Federated Learning Stochastic Gradient Descent (FedSGD) Client Side.

The server-side approach is essential for federated learning. It lets the models learn from a large data set, even if the data comes from many different people. Because of this, shared learning could help train machine learning models to work with private data.

Algorithm 2. Federated Learning Stochastic Gradient Descent (FedSGD) Server Side.

Servers initialize the global model first. This model can be pre-trained or randomly initialized. Federated averaging updates model parameters iteratively when client-side models update. Compiling local model modifications updates the global model. Server-side models

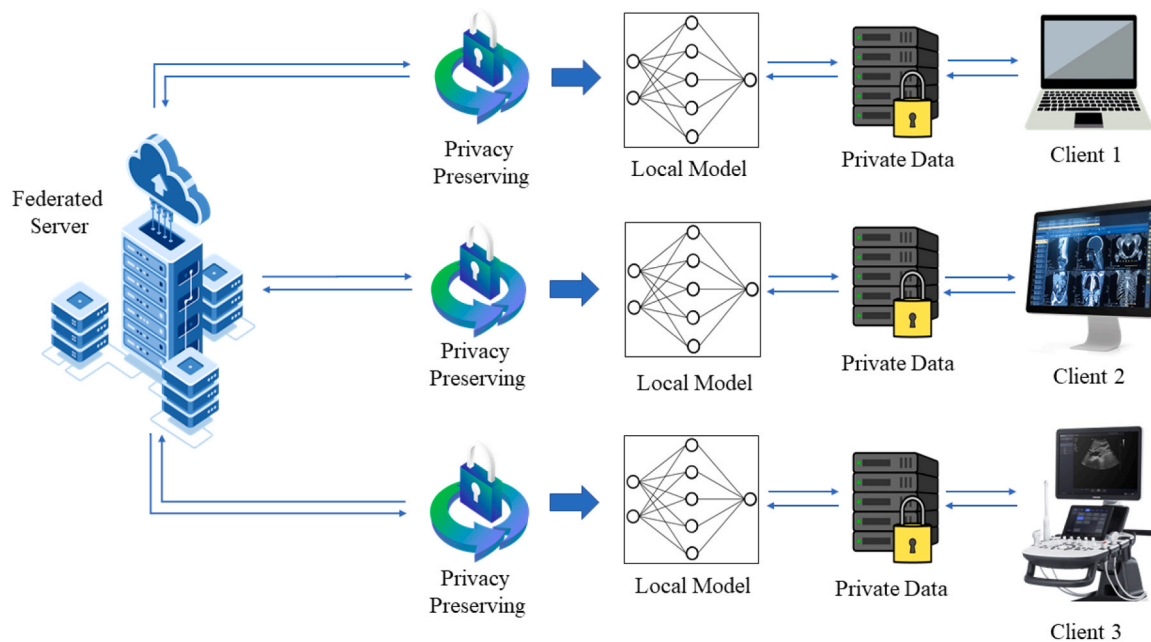


Fig. 10. The standard federated learning (FL) process involves a network of training nodes that receive a global model. These nodes then periodically submit their partially trained models to a central server for aggregation. The server returns a consensus model, which the nodes then use to continue their training (Long et al., 2015).

iterate until loss function convergence. Clients receive the server-side model after loss function convergence.

A federated deep learning model, SU-Net, was proposed to operate multi-scale information more efficiently (Yi et al., 2020). Several studies were conducted to improve the federated learning (FL) process. Tuladhar et al (Tuladhar et al., 2022). refined the learning process by ensembling the weight aggregation function. Mahlool et al (Mahlool et al., 2022). contextualized advancements to solve overhead limitations. Nalawade et al (Nalawade et al., 2022). aimed to enhance model aggregation based on performance, while Khan et al (Khan et al., 2022). introduced regularization techniques. Developing standard protocols and data formats among healthcare institutions is crucial to optimize the clinical application and promote collaboration.

FL is beneficial in the clinical field, as it effectively addresses data privacy concerns and enables collaborative model improvement (Rieke et al., 2020). Looking ahead, the field of FL aims to expand its capabilities in real-time, collaborative disease monitoring and management across different geographies. With the help of advancements in privacy-preserving technologies, FL could enable the creation of global healthcare models that are more inclusive of diverse populations and rare conditions. It is also expected to see the integration of FL with other emerging technologies like the Internet of Medical Things (IoMT), which could enhance remote diagnosis and patient monitoring. Additionally, FL has the potential to drive personalized medicine by utilizing decentralized data to tailor treatments to individual genetic and environmental factors, all while ensuring data security.

7. Clinical applications

Computer-aided detection (CAD) systems are increasingly being used in clinical applications to expedite laborious processes. A CAD system using AI was developed by Chen et al (Chen et al., 2023). to identify, grade, segment, and gain knowledge about gliomas. Neuroimages are commonly depicted using a visual attribute called the histogram of gradients (HOG). The CAD system utilizes a two-tier classification framework to differentiate between healthy individuals and patients, as well as between various grades of glioma, based on HOG characteristics. The system also provides tumor visualization through a semi-automatic

segmentation tool, which improves patient management and facilitates treatment monitoring. The two-level classification architecture achieved an area under the curve (AUC) of 0.921 and 0.806, respectively. This approach differs from other systems as it integrates diagnostic tools with a web-based interface to make it more adaptable for system implementation. To differentiate between brain MRI pictures with and without tumors, Saad et al (Saad et al., 2023). developed a graphical user interface (GUI). It not only displays the final classification result but also the results of each work step and each classifier's classification independently. The interface also provides functions such as brightness contrast adjustment and tumor encirclement. Ali et al (Ali et al., 2022b). developed an intelligent system that uses a support vector machine (SVM) classifier for diagnosing brain tumors with the help of MRI images. The system is capable of identifying and diagnosing brain tumors while also providing relevant information by calculating the number of pixels within the segmented tumor region. If a tumor is detected in a brain scan, the following step would involve performing tumor segmentation to determine the tumor's geometrical properties.

To effectively implement segmentation in clinical applications, several crucial steps must be considered. First and foremost, reliable and high-quality imaging is essential, particularly in reducing artifacts and maximizing the efficiency of image acquisition settings. It is also crucial to test these models on a wide range of real-world data to ensure that they can adapt to various scenarios. Additionally, the segmentation results should seamlessly integrate into the clinical workflow, providing healthcare providers with actionable data.

Adopting brain tumor segmentation tools into clinical practice requires regular validation, ongoing improvement, and adherence to ethical and regulatory standards. On the horizon, there are several exciting developments, including multi-modal data integration, better explainable AI, personalized medicine, and quantitative imaging diagnostic extraction. AI-driven surgical assistance and telemedicine will revolutionize patient care, while real-time processing, automated reporting, and improved data interoperability will streamline clinical processes.

8. Conclusions

In this study, a systematic literature review of the advancement of brain tumor segmentation in the context over the past few decades in terms of deep learning and federated learning has been presented. Upon conducting a thorough analysis of the existing literature, common methodologies, including pre-trained models, cascaded networks, ensembles, and multimodality are summarized. Focus was steered on CNN and its many structures and applications in medical imaging. Based on the investigation, the areas with existing research gaps were identified, allowing us to provide a path forward for this field.

The principal findings of this review are summarized as follows.

1. There are numerous segmentation techniques for brain tumors, but cascaded networks perform exceptionally well on tumor detection because of maximum feature extraction. In addition, ensembling techniques are more effective for accurate segmentation that yields balanced results.
2. Researchers typically calculate dice coefficient metrics for performance evaluation. Therefore, it is the primary evaluation criterion for comparing performance to others.
3. The BraTS challenge dataset is utilized primarily by maximum researchers. This dataset incorporates multimodal information for more efficient tumor segmentation. HGG and LGG samples are included in this dataset, along with the training and validation portions.
4. Integrating information from different sources can make it easier to communicate and make features more general. Inclusion or aggregation does not add new parameters, but it does not show how features are utilized. An attention mechanism can optimize feature expression using a small network, but it will also add new parameters and increase the computation cost.
5. Fusion and attention mechanisms can improve the segmentation performance more accurately on missing modalities. However, if any modality information is missing, then the invariant feature extraction helps to extract the info from current modality data.

In situations where access to medical data for training purposes is restricted in order to maintain privacy, Federated Learning (FL) presents a promising solution for developing models that are effective, precise, secure, stable, and unbiased. Federated learning effectively addresses the challenge of limited datasets for both training and testing purposes while simultaneously preserving the privacy of sensitive data. Numerous researchers were drawn to this, and much research is being conducted. Accurate labeling is a crucial aspect of medical demographic images. Several benchmark datasets, including the BraTS challenge datasets from 2012 to 2021, have been made accessible to researchers in this field to validate their work on openly available datasets. It is anticipated that there will be a surge in the utilization of Federated Learning (FL) for medical applications in the coming years. This will lead to the developing of more sophisticated protocols that offer enhanced security and privacy assurances. Furthermore, implementing FL technology to address practical challenges in the healthcare sector is expected to become a reality.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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