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Neural Network for Brain Tumor Detection and Segmentation in MRI: A Systematic Review of Convolutional Neural Networks and Diagnostic Accuracy

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Neural networks, brain tumor, MRI, convolutional neural networks, diagnostic accuracy

ABSTRACT

Abstract

Brain tumor detection and segmentation have seen remarkable advancements with the adoption of neural networks, particularly Convolutional Neural Networks (CNNs), which have achieved high diagnostic accuracy in magnetic resonance imaging (MRI). This study analyzes current AI applications for brain tumor diagnostics, identifying key advancements, challenges, and future research directions. Models like ACMINet and TransDoubleU-Net have reported exceptional accuracy, with metrics reaching up to 99.82%. Despite these successes, challenges persist, including reliance on limited and homogeneous datasets, issues with computational efficiency, and the need for explainable AI (XAI) tools to enhance model interpretability. A critical research gap is the absence of a comprehensive diversity index to ensure dataset representativeness, which affects the generalizability and robustness of AI models across diverse populations and tumor types. Furthermore, the underexplored potential of leveraging blood test biomarkers for non-invasive brain tumor diagnostics remains significant. Unlike imaging-based approaches, blood tests offer a cost-effective and easily accessible diagnostic alternative, yet there is a noticeable lack of publicly available datasets focused solely on biochemical data. This limitation restricts the development of AI models specifically designed to analyze blood test results, an area that holds great promise for advancing early detection and personalized treatment strategies. This systematic review highlights the importance of demographic and algorithmic factors in clinical settings, emphasizing the need for larger-scale meta-analyses and harmonization methods to diversify training datasets. Challenges such as feature selection for high-dimensional imaging data and the absence of standardized evaluation protocols further complicate the landscape. To address these gaps, this study proposes the development of a dataset diversity index, improved generalizability techniques, and the integration of advanced explainable AI methods. Future research should focus on these areas to advance AI-driven diagnostics, ensuring accuracy, robustness, and clinical relevance. This comprehensive evaluation underscores the transformative potential of AI in brain tumor detection and calls for collaborative efforts to overcome existing limitations and pave the way for improved patient outcomes.

1. INTRODUCTION

Rapid development in artificial intelligence (AI) and medical imaging have remarkably revolutionized the healthcare industry, especially in the domain of diagnostics. Among various medical imaging methods, Magnetic Resonance Imaging (MRI) stands out as a powerful tool for the detection and analysis of the brain. However, the interpretation of MRI scans is still a complex and time-consuming process, usually relying on the expertise of radiologists. Neural networks (NNs) have become a promising solution for enhancing diagnostic efficiency and accuracy.

1.1 Background

Brain tumors pose serious health risks due to high morbidity and mortality rates. Early detection and accurate tumor segmentation are critical for better treatment planning and prognosis. Traditional diagnostic methods often encounter limitations, such as the substantial time required for manual segmentation of Magnetic Resonance Imaging MRI scans. The integration of neural networks into this workflow has proven considerable possibility in overcoming these limitations. Neural networks, a part of machine learning, are designed to emulate the function of the human brain, learning patterns, and making decisions based on input data. In the area of brain tumor analysis, two primary tasks are addressed: detection and segmentation. Detection involves identifying the existence of a tumor in MRI scans, whereas segmentation indicates delineating and specifying the tumor boundaries for further analysis. Traditional neural networks, including convolutional neural networks (CNNs) and their variations, have shown outstanding capabilities in automating these tasks. Primary techniques employed in these models include feature extraction, pattern recognition, and pixel-wise classification. CNNs, for instance, utilize their hierarchical architecture to capture spatial and contextual features from MRI images, making them particularly appropriate for medical imaging applications. Other approaches, such as transfer learning and data augmentation, have been employed to overcome the challenges posed by limited annotated datasets and to improve model performance.

1.2 Aims and Objectives of the Review

This systematic review aims to provide a comprehensive overview of the current advancements in brain tumor detection and segmentation using neural networks, with a particular focus on Convolutional Neural Networks (CNNs). It seeks to explore the role of neural networks in analyzing MRI images for tumor detection and segmentation, categorizing key findings by dataset diversity, model architecture, performance metrics, and the integration of Explainable AI (XAI). The objective is to identify the strengths of current approaches, highlight limitations that still need to be addressed, and provide insights into future trends in the field. Specifically, this review aims to:

Assess the dominance of CNNs and their variants, such as U-Net,u- in brain tumor segmentation and classification.

Examine the advancements in hybrid and transformer-based models, identifying their potential benefits in improving detection accuracy, particularly for complex tumor types.

Investigate the adoption and effectiveness of Explainable AI methods like Grad-CAM and LIME, exploring how these approaches improve model interpretability, especially in clinical applications.

Highlight the challenges and limitations related to dataset diversity, real-time performance metrics, and the generalizability of AI models.

Propose recommendations for future research directions, focusing on addressing gaps in the literature and advancing the practical use of AI for brain tumor detection and segmentation.

1.3 Scope of the Review

This review encompasses studies that focus on the application of neural networks, particularly CNNs, in the detection and segmentation of brain tumors using MRI imaging. It covers a range of methodologies, from classic CNN architectures to recent innovations such as hybrid models and transformer-based networks, which have been proposed to improve segmentation accuracy for small or irregular tumors. Additionally, this review explores the integration of Explainable AI (XAI) techniques in brain tumor analysis, with a particular focus on methods like Grad-CAM and LIME. These tools help make AI model decisions more transparent, a critical factor in clinical settings where understanding the basis for a diagnosis is necessary.The review also considers the challenges in model deployment, including issues related to computational overhead, real-time performance, and the need for more diverse and clinically representative datasets.

Furthermore, the review highlights the limitations of previous studies, including the reliance on curated datasets and the lack of real-world variability. It proposes that future research should address these gaps, emphasizing the need for more robust models. The review also stresses the importance of incorporating longitudinal data for tracking tumor progression and treatment responses over time, a direction that has received limited attention in prior work.

In summary, the scope of this review is to provide an in-depth analysis of the current landscape of AI-based brain tumor detection and segmentation, while also pointing to critical areas for further development and improvement in the field.

2. RELATED WORK

2.1 Literature Review

Neural networks have revolutionized the field of brain tumor diagnostic and segmentation in MRI images, with Convolutional Neural Networks (CNNs) being the most widely used architecture. Alalwan et al. [1] proposed a novel approach combining synthetic generative adversarial networks (GANs) with federated convolutional neural networks (Federated-CNNs) to enhance the accuracy and privacy of brain tumor identification by utilizing MRI data with synthetic augmentation. Their approach achieved an exceptional accuracy of 99.82%, outperforming existing models like Inception-V3 and ResNet-18. However, the study highlighted challenges related to class imbalance.

In another study [2], Ramakrishnan et al. proposed a hybrid CNN architecture combining InceptionV3, ResNet-50, VGG16, and DenseNet optimized with oneAPI for tumor classification. Their model was tested on 3,929 MRI images from TCGA LGG collection, achieving an accuracy of 96.2%.

Despite its success, the study noted limitations in clinical validation.

Xu and Mohammadi [3] employed Mobilenetv2 optimized by Contracted Fox Optimization Algorithm (MN-V2/CFO) to enhance the accuracy of tumor detection. Their model utilized Figshare dataset achieving an accuracy of 97.32, a precision of 97.68%, and an F1-score of 86.22 % but fell short in sensitivity (80.12%). Furthermore, the proposed model has several limitations to be addressed. First, the model strongly relies on the quality, diversity, and representativeness of the dataset used for training and evaluation. Second, model validation on external datasets is essential for generalizability. Third, challenges related to interpretability of the model's predictions need to be considered. Fourth, the model requires major computational resources which might limit its practical implementation in resource-constrained environments. Lastly, further clinical validation is crucial to assess the model's real-world effectiveness.

The authors in reference [4] proposed a Convolutional Long Short-Term Memory (ConvLSTM) model to detect anomalies in 3D MRI scans. The model utilized three main datasets the Brain Tumor Segmentation Challenge (BRATS), the Federated Tumor Segmentation Challenge (FETS), and the Medical Segmentation Decathlon (MSD). Their approach achieved an impressive accuracy of 98.9%.

Zafar et al. [5] introduced the Enhanced TumorNet model, combining YOLOv8s for detection and U-Net for segmentation. Their model utilized The Cancer Imaging Archive (TCIA) and the Cancer Genome Atlas (CGA) datasets achieving a precision of 97.8%, an accuracy of 96.4%, F-1 score of 96.3 %, ROC-AUC score of 98.5 % but felling short in specificity (89.1 %) and recall (95.2 %). Additionally, the model encounters several limitations that reflect its practical implications. These include the reliance on high-quality datasets, substantial computational resource requirements, potential trade-offs between accuracy and real-time performance, and other challenges associated with generalizability, overfitting, and interpretability.

Al-Fakih et al. [6] focused on synthesizing Fluid Attenuated Inversion Recovery (FLAIR) MRI sequences using a squeeze attention GAN integrated with nnU-Net. Their model demonstrated significant enhancement in segmentation accuracy, with the Dice Similarity Coefficient (DSC) increasing from 0.688 to 0.892. Moreover, the synthesizing model utilized BraTS 2021dataset, BraTS 2020 dataset for validation and BraTS Africa 2023 dataset for training. While findings demonstrate the potential of the proposed method for FLAIR image synthesis, attaining near-perfect synthesis remains difficult. Improvements may demand a larger training dataset and a more complex model, which would, in turn, require greater computational resources.

Nazir et al. [7] developed a customized CNN incorporating Explainable AI (XAI) tools such as SHAP, LIME, and Grad-CAM to classify brain MRI images into tumorous and non-tumorous categories. Using the BR35H dataset containing 3,060 images, their model achieved a validation accuracy of 98.67%, with precision and recall scores at 98.5%. However, the study faced several limitations, including reliance on a single dataset, binary classification that does not differentiate tumor subtypes, and occasional ambiguity in XAI visualizations.

Hanumanthu and Raghuram [8] proposed a fine-tuned EfficientNetV2 model for multigrade tumor classification. The Figshare dataset, consisting of 3,064 images across four tumor types (glioma, meningioma, pituitary, and non-tumor), was utilized. Grad-CAM was employed to enhance model interpretability, and the model achieved a test accuracy of 98.48%, with recall and sensitivity metrics exceeding 98%. Despite these achievements, the study's reliance on publicly available datasets without real-world validation raises concerns about its clinical generalizability.

Nguyen-Tat et al. [9] enhanced segmentation performance by integrating Vision Transformers and guided attention mechanisms into a U-Net architecture. Their approach utilized augmented MRI datasets, achieving a Dice Similarity Coefficient (DSC) above 90% for small and irregular tumor regions. The study demonstrated robustness against noisy and low-quality images, a notable advancement in real-world applicability. However, the complexity of the model led to high computational demands, and its reliance on curated datasets limited its generalizability to broader clinical scenarios.

Wadud et al. [10] explored a support value-based adaptive deep neural network (SDNN) for binary tumor classification. The BMRI dataset, containing only 70 images, was used for evaluation. The SDNN achieved a classification accuracy of 96% and excelled in extracting entropy and geometric features. Nonetheless, the small dataset size restricted the model's ability to generalize across diverse populations, and challenges in modeling tumor microenvironments were also noted.

Bougueura et al. [11] implemented Manta Ray Foraging Optimization (MRFO) for hyperparameter tuning in a CNN architecture to classify brain tumors. Using datasets such as BRATS and TCIA, the model achieved an accuracy of 98.9%. The study highlighted computational efficiency as a major advantage of MRFO; however, issues such as limited dataset diversity and the lack of interpretability tools like Grad-CAM restricted its clinical applicability.

The study [12] utilizes a brain tumor MRI dataset from Kaggle, with training and test sets comprising 1321 glioma, 1339 meningioma, 1595 no tumor, and 1457 pituitary images in a 3:1 ratio, ensuring diverse and balanced evaluation. The proposed method integrates attention mechanisms, depth hashing, and a novel ternary loss function within a Pytorch-based framework to enhance feature representation and classification accuracy. Experiments conducted on a GeForce RTX 2080 Ti achieved improved image retrieval metrics, with mHR increasing to 0.7783, mAP to 0.752246, and mRR to 0.956721, outperforming the ATH method. The model's real-world application in hospital settings demonstrated its reliability, but limitations include the need for broader dataset validation, optimization of attention modules, computational complexity, and interdisciplinary collaboration to enhance scalability and clinical applicability. The study underscores the effectiveness of advanced techniques in improving diagnostic precision while addressing challenges in resource constraints and generalization.

The study [13] utilized three datasets for brain tumor MRI analysis, including Hennes (2023) with 4,445 scans, Feltrin (2023a) with 4,449 categorized images, and Feltrin (2023b) with 44 classes of T1, T1C, and T2 images, addressing data imbalance through augmentation and tokenization techniques while maintaining confidentiality. The intervention incorporated knowledge distillation, transformers, tripartite attention mechanisms, cross-modal knowledge distillation, and lightweight CNNs to enhance diagnostic accuracy and computational efficiency in resource-limited settings. The TriA model demonstrated superiority with improved metrics, lower losses, and high accuracy across datasets, while class weighting enhanced the Deep CNN model's Top-1 Accuracy from 0.7508 to 0.8013. Despite leveraging NVIDIA A100 GPUs for efficiency, limitations persist, including overfitting risks, data scarcity, computational constraints, potential data leakage, and challenges in model complexity and interpretability, highlighting the need for balance between accuracy and resource usage.

The study [14] utilized the BraTS 2020 dataset, containing 3D MRI scans from 369 glioma patients, preprocessed for consistency and annotated by neuroradiologists, as a benchmark for training and assessing the GAIR-U-Net model. Incorporating inception residual blocks, dilated convolutions, and guided attention mechanisms, the model achieved Dice scores of 0.8796 for Whole Tumor, 0.8634 for Tumor Core, and 0.8441 for Enhancing Tumor, demonstrating its segmentation capabilities. Cross-validation on the BraTS 2021 dataset showed robust generalization with slightly lower Dice scores. The model outperformed state-of-the-art methods like TransBTS and MRA-UNet but faced challenges with small tumor segmentation, boundary delineation, multimodal data integration, and computational constraints, requiring 16.58 minutes per epoch. Future directions include deeper feature extraction, hybrid learning techniques, and 3D transformers to enhance performance while addressing overfitting risks and clinical applicability.

The study [15] utilized CT and MRI images from The Cancer Imaging Archive (TCIA) to develop and test the Multimodal Fusion Network (MFNET) for brain image classification, employing image fusion techniques such as the auto-encoder-based nuclear norm method to enhance diagnostic accuracy. The MFNET integrates multimodal information with CNN architecture for feature extraction and classification, demonstrating superior performance in metrics like MI, SSIM, Piella, and UIQI compared to standard fusion techniques. The fused images exhibited enhanced structural and textural information, improving their utility for medical analysis. However, limitations include computational complexity, restricted testing on specific hardware, generalization concerns due to reliance on the TCIA dataset, less effective content retention compared to other methods, and additional complexity introduced by the network's architecture. These findings highlight the potential of MFNET while emphasizing the need for further validation and optimization.

The study [16] focuses on brain tumor segmentation using datasets like BraTS and TCIA, emphasizing MRI data for its precision and non-invasive nature. Challenges such as limited data availability are addressed with novel augmentation techniques, radiogenomic integration, and robust fusion strategies. Advanced methods include RLSegNet for reinforcement learning, M2FTrans for incomplete modalities, and transformer-based models, all achieving significant improvements in segmentation accuracy. Results show models like ACMINet and TransDoubleU-Net delivering state-of-the-art performance with high Dice Similarity Coefficients, while U-Net-based architectures remain dominant for accurate tumor delineation. Limitations include computational efficiency concerns, reliance on limited datasets, interpretability issues, and challenges with high-dimensional data and generalization. The findings highlight advancements in segmentation accuracy while identifying areas requiring further research and optimization.

The study [17] provides an overview of AI methods for brain tumor segmentation in MRI images. It examines supervised, unsupervised, and deep learning models such as U-Net, ResUNet, and Inception V3, which have demonstrated high accuracy in tumor detection and segmentation. The study references widely used datasets like BraTS and employs cross-validation for model evaluation. It summarizes advancements in the field and highlights the potential of AI in improving diagnostic accuracy.

The study [18] introduces a deep learning-based approach for brain tumor diagnosis using MRI images. It combines AlexNet for feature extraction, an Extreme Learning Machine (ELM) for classification, and the Amended Grasshopper Optimization Algorithm (AGOA) for parameter tuning. Tested on a dataset of 20 glioblastoma patients, the method achieved 96% accuracy, 94% sensitivity, and 96% specificity, outperforming other techniques. However, the study notes three main limitations: the small and homogeneous dataset limits generalizability to other tumor types and diverse populations, the approach depends heavily on high-quality MRI images, and the use of a linear activation function in the ELM network may reduce its ability to capture complex data relationships.

The study [19] aims to enhance brain tumor classification by using the Br35H dataset, which includes 3000 MRI images, half containing tumors and half without. The study enhances image quality using GFPGAN and Real-ESRGAN, and applies deep CNN models like VGG16, DenseNet-169, EfficientNet-B3, and EfficientNet-B5. Ensemble learning techniques such as weighted sum, fuzzy rank, and majority voting are used to improve results. The dataset is divided into

70% for training and 30% for validation and testing. The best results achieved are 100% accuracy with GFPGAN-enhanced images and 99.83% with Real-ESRGAN-enhanced images, using the top 5 and 2 classifiers, respectively.
However, the study has several limitations: CNN models have limited complexity, which affects classification accuracy; the computational expense of transfer learning and ensemble methods makes the process resource-intensive; there is a lack of guidance in selecting algorithms for ensemble learning, potentially leading to inefficiencies; and the use of certain activation functions may limit the model's ability to capture complex data relationships.

The study [20] aims to enhance brain tumor classification by integrating pre-trained CNN models (such as VGG16, ResNet50, and InceptionV3) with machine learning algorithms like SVM, Random Forest, and KNN. The CNNs are used to extract features from MRI images, which are then classified using machine learning models. The study utilizes an MRI dataset with tumor and non-tumor categories, and feature selection is performed using CNN-based feature extraction, with validation through cross-validation or train-test splits. The best results are achieved by combining CNNs with machine learning, surpassing the performance of either method used alone. However, there are several limitations: traditional machine learning techniques often struggle with achieving high accuracy; the complex nature of medical data presents challenges for prediction models; existing methods have difficulties with precise tumor segmentation; the feature maps have limited utilization of contextual and spatial information; and segmentation may be inaccurate due to variability in tumor size and shape. Despite these challenges, the approach shows strong potential for improving brain tumor classification accuracy.

The study [21] focuses on advanced brain tumor segmentation using a newly developed deep learning model, 3D UNet, enhanced with Contextual Transformers (CoT) and Double Attention (DA). The model, applied to the BraTS 2019 and 2020 datasets, which include T1, T1c, T2, and FLAIR MRI scans, improves tumor boundary refinement by capturing long-range dependencies and emphasizing important spatial and channel features. The data was split randomly with 80% for training and 20% for testing, and 3-fold cross-validation was performed. The model achieved high Dice scores of 82%, surpassing existing models, with specific results of 89.2% for WT, 84.6% for TC, and 9% for ET on BraTS 2019. While the approach significantly improves accuracy, it comes with notable limitations: the integration of CoT and DA increases model complexity and training time; training time approximately doubled for the BraTS 2019 and 2020 datasets; and the longer training times may hinder deployment on hardware-constrained devices.

The study [22] employs deep learning techniques, specifically Convolutional Neural Networks (CNNs), for brain tumor classification using MRI images. The dataset, publicly available on Kaggle, includes 1321 glioma, 1339 meningioma, and 1457 pituitary tumor images, with a testing set comprising 300 glioma and 306 meningioma images. The model achieved 98% accuracy, with precision, recall, and F1-scores ranging from 97% to 98%, and ROC-AUC scores between 99% and 100% for tumor categories. Grad-CAM visualizations were utilized to improve the interpretability of the model and offer a clearer understanding of its decision-making process. This model outperformed previous studies in terms of accuracy and precision, aiding radiologists in accurate brain tumor classification and improving decision-making for treatment options. The model's improved accuracy can streamline the diagnostic process in clinical settings and contribute to better patient care outcomes. However, limitations include the reliance on high-quality, well-annotated datasets, potential variation in performance across demographic groups, the need for extensive computational resources, and the requirement for hyperparameter tuning to optimize performance. Additionally, further research into Grad-CAM interpretation is necessary.

The study [23] utilized the BRATS2014 and BTD20 databases for brain tumor diagnosis. It involved image pre-processing to differentiate the brain region from the background, followed by image segmentation using Convolutional Neural Networks (CNN) and Genetic Algorithms (GA). Feature extraction was carried out using Multi-Linear Principal Component Analysis (MPCA), and classification was performed with Artificial Neural Networks (ANN) and GA. The method achieved a remarkable performance, attaining 98.6% accuracy on the BRATS2014 dataset and 99.1% accuracy on the BTD20 dataset. These results indicate a minimum enhancement of 1.1% over previously established techniques. The genetic algorithm optimized the CNN configuration with a fitness value of 0.96115. This novel method enhances MRI image segmentation quality and addresses computational complexity in CNN configuration. The use of genetic algorithms for hyperparameter optimization contributed to the high accuracy of tumor classification, with results of 98.6% and 99.1%.

The study [24] utilized a diverse dataset of 1747 MRI brain scan images, including both tumor and non-tumor cases curated from Kaggle. It applied image preprocessing and multilevel thresholding techniques, along with deep learning methods like Deep Convolutional Neural Networks (DCNN) and multi-layered perceptron algorithms, to enhance brain tumor detection. The model achieved 92% accuracy, categorizing various brain tumor types and normal cases. It also integrated into a user-friendly smartphone app, MediScan, which provides heatmap visualizations and diagnostic reports. However, the model's performance relies on dataset diversity and size, requires significant computational resources, and faces challenges in interpretability due to deep learning complexity. Additionally, there is limited robustness in capturing rare cases, and continual data refinement is needed to improve its accuracy and reliability.

The study [25] utilized two datasets: 4,600 X-ray images divided into two classes and 3,064 MRI images categorized into three groups. The Convolutional Neural Network (CNN) was used for classification, with Transfer Learning (TL) and Manta Ray Foraging Optimization (MRFO) employed for model enhancement and hyperparameter optimization. The model achieved 99.96% accuracy for X-rays and 98.64% accuracy for MRIs, with VGG16 performing best on the two-class dataset and Xception excelling in the three-class dataset. Despite its high performance, the framework faced challenges, including high computational demands from advanced augmentation methods, a lack of explainable AI for model interpretability, and dataset distribution imbalance that requires more diverse examples. Misclassifications were manually reviewed for improvement.

The study [26] utilized two datasets: Dataset 1, which included 3,064 MRI slices from 233 patients with brain tumors, and Dataset 2, containing 152 MRI slices with both healthy and abnormal images. A 23-layer Convolutional Neural Network (CNN) architecture with transfer learning using the VGG16 model was employed for classification. The models achieved up to 97.8% classification accuracy, with tumor types like meningioma, glioma, and pituitary tumors achieving accuracies of 96.7%, 97.2%, and 99.5%, respectively. However, the study faced limitations such as the need for substantial annotated images for robust model training, limited availability of accurately annotated data, and issues with overfitting when working with small datasets. The models were not validated on actual clinical data, and pre-trained models showed bias towards larger sample classes. Despite high accuracy, CNNs struggled with slight image variations. Data augmentation was used to improve performance on the limited datasets.

2.2 Gap Analysis

The systematic review and meta-analysis of artificial intelligence (AI) models for brain tumor detection and segmentation in MRI have highlighted several critical research gaps.

First, there is an urgent need to develop a comprehensive diversity index that evaluates dataset representativeness, ensuring it adequately captures variability in tumor types and patient demographics.

Second, the influence of demographic factors including age, gender, and ethnicity on the performance and generalizability of AI models remains insufficiently explored and requires further investigation.

Additionally, larger-scale meta-analyses that encompass a variety of tumor types are necessary to achieve a more comprehensive understanding of AI model performance across different clinical scenarios.

There is also a need to explore harmonization methods for diversifying datasets to address biases and imbalances in training data.

Lastly, it is essential to gain a deeper understanding of algorithm-related technical factors, particularly within real-world clinical settings, to bridge the gap between experimental success and practical implementation.

Many models, such as SCNet, have been evaluated on limited datasets, which may not capture the full variability of real-world clinical data, hindering the generalizability and robustness of the models when applied to diverse patient populations. Although M2FTrans has shown improvements in handling incomplete modalities, existing fusion strategies are still not ideal, indicating a need for more robust methods to effectively integrate incomplete or missing data in multi-modal segmentation tasks. There is a lack of detailed discussion on the computational efficiency of advanced models, such as those using transformers and attention mechanisms, which is crucial as it affects the feasibility of deploying these models in real-time clinical environments. Some models, particularly those employing complex architectures like self-supervised learning and transformers, offer limited insights into their interpretability, which is significant for clinical adoption as healthcare professionals require transparent models to trust and understand the decision-making process. Despite achieving high performance in controlled settings, there is limited exploration of how these models perform on real-world clinical data, and bridging this gap is essential for transitioning from research to practical clinical applications. Lastly, the complexity of feature selection in high-dimensional medical imaging data remains a challenge, affecting the accuracy and efficiency of segmentation models and necessitating more effective strategies for managing and processing such data.

A significant gap exists in the integration of multimodal data, particularly combining blood test biomarkers with MRI scans. Most studies have focused exclusively on imaging-based methods, overlooking the complementary diagnostic potential of blood biomarkers. Blood tests provide a cost-effective and non-invasive way to detect systemic physiological changes linked to tumor presence and progression. By integrating this information with the spatial and structural details offered by MRI scans, diagnostic accuracy could be substantially improved, ultimately enhancing patient outcomes.

2.3 Discussions of the key contributions

This systematic review and meta-analysis of artificial intelligence (AI) models for brain tumor detection and segmentation in MRI provide significant contributions to advancing the field by examining advancements in neural networks for brain tumor detection and segmentation using MRI data, while highlighting significant gaps in current research.

Critical gaps have been identified, such as the lack of diversity in datasets, limited consideration of demographic factors (age, gender, ethnicity), and insufficient exploration of real-world performance. Also, the overwhelming focus on imaging-only approaches. These gaps highlight key areas for future research to enhance the robustness and generalizability of AI models.

In term of dataset representativeness and harmonization, this review emphasizes the importance of dataset diversity to capture variability in tumor types and patient demographics. We propose developing a comprehensive diversity index and adopting harmonization methods to address biases and imbalances in training data. These recommendations aim to improve the inclusiveness and fairness of AI models.

Improving Generalizability and Robustness: Many current models have been evaluated on limited datasets that fail to reflect real-world clinical data. Our review highlights the need for larger-scale studies and meta-analyses that include diverse tumor types to ensure models perform reliably across various clinical scenarios. This is essential for translating AI advancements into practical applications.

3. METHODOLGY

3.1 Research Question

In this study, the effectiveness of convolutional neural networks (CNNs) in enhancing diagnostic accuracy for brain tumor detection using MRI images was evaluated. The population of interest consists of patients undergoing brain tumor diagnosis, specifically through the use of MRI imaging. The exposure being examined is the implementation of CNNs as a diagnostic tool to detect and classify brain tumors from these MRI scans. The primary outcome of interest is the improvement in diagnostic accuracy when using CNNs, compared to traditional diagnostic methods, such as manual analysis by radiologists. This methodology aims to assess whether CNNs can offer more precise, consistent, and timely diagnoses, thereby improving the overall detection process for brain tumors.

3.2 Research Strategy

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was used to conduct a comprehensive and structured review of the existing literature on the application of convolutional neural networks (CNNs) in enhancing diagnostic accuracy for brain tumor detection using MRI images. Figure 1 illustrates the process of conducting a systematic review. It shows the number of records identified after the initial search, the removal of irrelevant publication types, the screening of titles and abstracts, and the full-text assessment for eligibility. The chosen papers were subsequently classified as either included in the analysis or excluded based on predetermined eligibility criteria. This approach ensures a comprehensive review of the literature on the use of convolutional neural networks (CNNs) to improve brain tumor diagnosis using MRI scans.

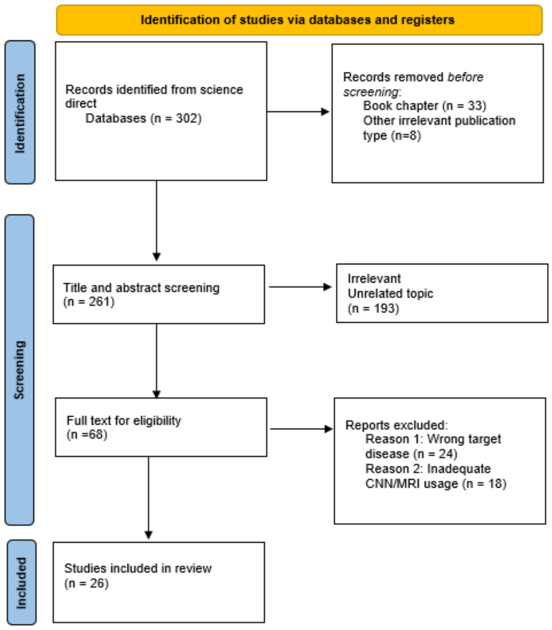

Figure 1. The PRISMA methodology flowchart

ScienceDirect was selected as the primary database. The search strategy included the following keywords: “Neural Network,” “Brain Tumor,” “MRI,” “Convolutional Neural Networks,” and “Diagnostic Accuracy.” Filters were applied to cover publications from the years 2022 to 2025. The search strategy used is demonstrated in Figure 2.

Search Strategy Template	
Research Question	How effective are convolutional neural networks (CNNs) in enhancing diagnostic accuracy for brain tumor detection using MRI images
Generate Search Terms and Keywords	(Neural Network)AND (Convolutional Neural Networks) AND (Brain Tumor) AND (MRI) AND (Diagnostic Accuracy)
Record Search Process	
Date of Search	15/11/24
Search Query Used	*"detection " AND "neural networks" AND "brain tumor"*
Filters Applied	since 2022 - 2025
Database	**Number of Studies Found**
ScienceDirect (www.sciencedirect.com)	2,430 results
Date of Search	15/11/24
Search Query Used	*"detection" AND "neural networks "AND "convolutional neural networks" AND "brain tumor"*
Filters Applied	since 2022 - 2025
Database	**Number of Studies Found**
ScienceDirect (www.sciencedirect.com)	1,823 results
Date of Search	16/11/24
Search Query Used	*"Neural Network" AND "Convolutional Neural Network" AND "Brain Tumor"AND "MRI" AND "Diagnostic Accuracy"*
Filters Applied	Last 3 years
Database	**Number of Studies Found**
ScienceDirect (www.sciencedirect.com)	302 results

Figure 2. The search strategy

3.3 Inclusion and Exclusion Criteria

To ensure that only relevant studies were selected for the research question "How effective are convolutional neural networks (CNNs) in enhancing diagnostic accuracy for brain tumor detection using MRI images?”, “The study selection process adhered to the following inclusion and exclusion criteria:

Inclusion Criteria

Study Focus:

The study must focus on brain tumor detection, classification, or segmentation using neural networks, particularly Convolutional Neural Networks (CNNs) or their variants (such as U-Net). Studies involving hybrid models that combine CNNs with other techniques like transformers or traditional machine learning methods are also included.

Scope:

Studies explicitly focus on improving or analyzing diagnostic accuracy, classification, or detection performance.

Timeframe:

Studies published within 2022-2025 to ensure the relevance of technology and methods.

Language:

Studies published in English.

Population:

Studies involving datasets or experiments focusing on human brain tumors.

Exclusion Criteria

Unrelated Topics:

Studies focus on tumors in other body parts or diseases unrelated to brain tumors.

Technology Scope:

Studies that did not utilize MRI for brain tumor detection, or those that failed to combine MRI with other imaging modalities or methods, were excluded from consideration**.**

Publication Type:

Book chapters and other irrelevant publications were excluded.

3.3 Quality Assessment

To assess the quality and risk of bias of the included studies, we have assigned four key domains: **Reliance on Single Dataset**, **Performance Reporting**, **Generalizability**, and **Model Description**. Each domain was assessed for potential bias and classified as either **Low**, **High**, **Unclear**, or **No Information**. The first domain considered is **Reliance on Single Dataset (D1)**, which evaluates whether studies depended solely on one dataset, potentially limiting generalizability. The second domain, **Performance Reporting (D2),** examines whether sufficient performance metrics, such as accuracy, sensitivity, and specificity, were provided to assess the reliability. The third domain, **Generalizability (D3),** assesses the extent to which study findings can be applied to other datasets or real-world scenarios. Lastly, the **Model Description (D4)** domain reviews the clarity and detail of the neural network's architecture and methodology to ensure reproducibility. The results of the quality assessment are visually summarized in Figure 3 below, generated using the **robvis** tool [28].

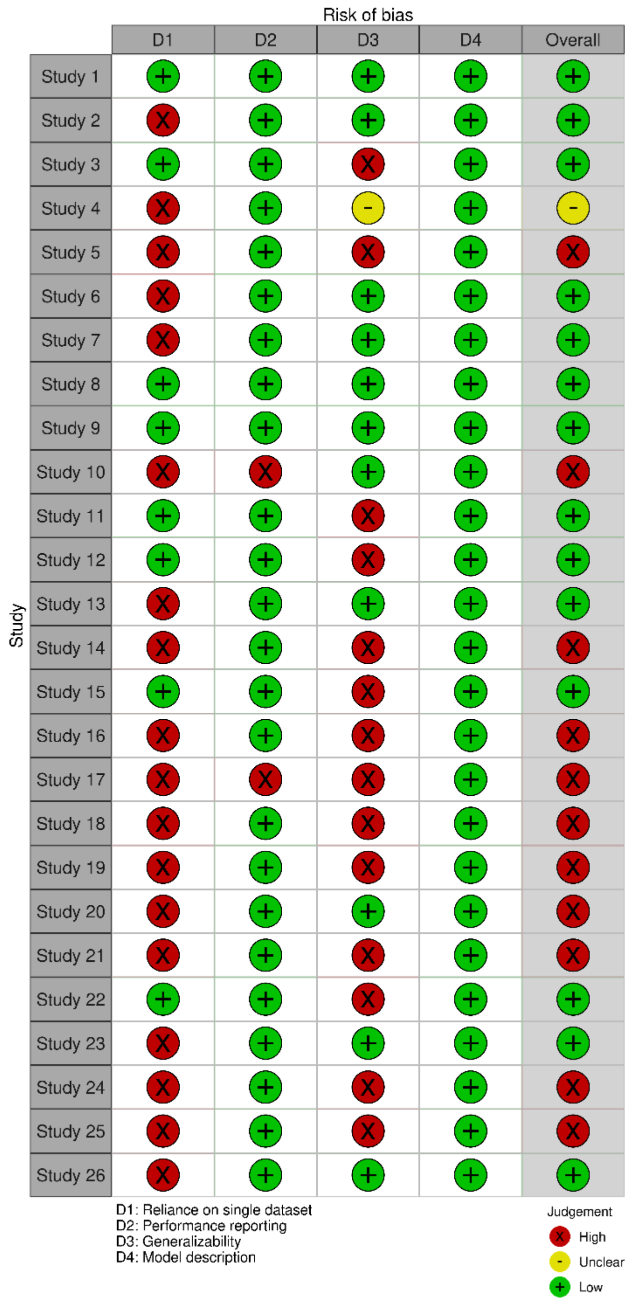

Figure 3. Risk of Bias Assessment Across Included Studies

3.3 Data Extraction and Synthesis

Data Extraction

Reference	Author(s)	Year of Publication	Title	Country	Dataset Collection (Samples)	Intervention/ Technology	Results	Limitations (If available)
[1]	Nasser Alalwan, Ayed Alwadain, Ahmed Ibrahim Alzahrani, Ali H. Al-Bayatti, Amr Abozeid, Rasha M. Abd El-Aziz	2024	Advancements in brain tumor identification: Integrating synthetic GANs with federated-CNNs in medical imaging analysis	Saudi Arabia, UK, Egypt	MRI data with synthetic augmentation	"Integration Synthetic Generative Adversarial Networks with federated Convolutional Neural Networks in medical imaging analysis."	Achieved an accuracy of 99.82%, outperforming existing models like Inception-V3 and ResNet-18.	Imbalance in class distribution within the dataset.
[2]	Akshay Bhuvaneswari Ramakrishnan, M. Sridevi, Shriram K. Vasudevan, R. Manikandan, Amir H. Gandomi	2024	Optimizing brain tumor classification with hybrid CNN architecture: Balancing accuracy and efficiency through oneAPI optimization	India, Australia, Hungary	3929 MRI images from TCGA LGG collection	Hybrid CNN architecture implementing InceptionV3, ResNet-50, VGG16, and DenseNet and optimized with oneAPI	Achieved an accuracy of 96.2 %.	The lack in clinical validation.
[3]	Lu Xu, Morteza Mohammadi	2024	Brain tumor diagnosis from MRI based on Mobilenetv2 optimized by contracted fox optimization algorithm	China, Iran, Iraq	Figshare MRI dataset	"MobileNetv2 optimized with Contracted Fox Optimization Algorithm (MN-V2/CFO)."	Achieved a precision of 97.68 %, an F1-score of 86.22 %, a sensitivity of 80.12 %, and an accuracy of 97.32 %.	"The sensitivity is considered low. Dataset Limitations. Generalizability. Interpretability. Computational Resources. Clinical Validation."
[4]	Anuradha Durairaj, E.S. Madhan, M. Rajkumar, Syed Shameem	2024	Optimizing anomaly detection in 3D MRI scans: The role of ConvLSTM in medical image analysis	India	BRATS, FETS, and MSD datasets	ConvLSTM model for 3D anomaly detection	Achieved an accuracy of 98.9% in detecting anomalies.	NONE
[5]	Wisal Zafar, Ghassan Husnain, Abid Iqbal, Ali Saeed Alzahrani, Muhammad Abeer Irfan, Yazeed Yasin Ghadi, Mohammed S. AL-Zahrani, Ramasamy Srinivasaga Naidu	2024	Enhanced TumorNet: Leveraging YOLOv8s and Unet for superior brain tumor detection and segmentation utilizing MRI scans	Pakistan, Saudi Arabia,UAE	TCIA and CGA datasets	YOLOv8s for detection and U-Net for segmentation	Achieved a precision of 97.8 %, accuracy of 98.6 %, recall of 95.2 %, F-1 score of 96.3 %, specificity of 89.1 %, and ROC-AUC score of 98.5 %.	"The specificity and recall are considered low. Dependency on high-quality data. Computational Resources. Generalizability. Overfitting. Interpretability.. Limited Dataset Diversity Trade-offs between accuracy and real-time performance. Lack of Cross-Modality Validation"
[6]	Abdulkhalek Al-Fakih, Abdullah Shazly, Abbas Mohammed, Mohammed Elbushnaq, Kanghyun Ryu, Yeong Hyeon Gu, Mohammed A. Al-masni, Meena M. Makary	2024	FLAIR MRI sequence synthesis using squeeze attention generative model for reliable brain tumor segmentation	Egypt, South Korea, USA	BraTS 2021, BraTS 2020, BraTS Africa 2023	Squeeze attention GAN with nnU-Net	Improved segmentation accuracy (Dice similarity coefficient (DSC) from 0.688% to 0.873%).	"Computational resources. Dependency on synthetic sequence quality. Achieving ear-perfect synthesis remains challenging. Required a larger training dataset and increased model complexity."
[7]	Md Imran Nazir, Afsana Akter, Md Anwar Hussen Wadud, Md Ashraf Uddin	2024	Utilizing customized CNN for brain tumor prediction with explainable AI	Bangladesh	BR35H dataset (3060 MRI images)	Customized CNN with SHAP, LIME, Grad-CAM explainable AI techniques	Training accuracy of 100%, validation accuracy of 98.67%, and high precision and recall at 98.5%.	Previous studies had low accuracy in brain tumor detection. Lack of XAI techniques for model transparency and trust. Model trained on only one dataset limits robustness. Current model only classifies binary outcomes (tumorous vs. non-tumorous). Does not differentiate between specific tumor types.

[8]	Pallavi Priyadarshini, Priyadarshi Kanungo, Tejaswini Kar	2024	Multigrade brain tumor classification in MRI using Fine-Tuned EfficientNet	India	Three datasets: 1. Figshare dataset with 3064 T1-weighted images (four classes); 2. Dataset with over 3200 MRI scans (12 categories: tumor types and imaging planes); 3. Customized collection with 44 brain tumor classes (T1, contrast-enhanced T1, T2 MRI).	Fine-tuned EfficientNet with Grad-CAM visualization	Achieved average test accuracy of 98.48%, recall of 98%, and sensitivity of 98.71%.	NONE
[9]	Mohamad Abou Ali, Fadi Dornaika, Ignacio Arganda-Carreras, Rejdi Chmouri, Hussien Shayeh	2024	Enhancing MRI brain tumor classification: A comprehensive approach integrating real-life scenario simulation and augmentation techniques	Spain, Lebanon	BT-MRI dataset and BCD-MRI dataset	Vision Transformers, ImageNet models, advanced augmentation techniques	Initial accuracy of 100%; robustness improved through augmentation.	Variability in image quality affects model reliability. Motion artifacts from patient movement compromise accuracy. Intrinsic noise in MRI images limits generalizability.
[10]	B. Raghuram, Bhukya Hanumanthu	2023	Brain tumor image deep learning	India	IoMT-based clinical image database	Support value-based adaptive deep neural network (SDNN)	Outperformed existing approaches in classification accuracy.	Developing effective treatments for brain tumors is complex. Detecting individual stems in the brain is challenging. Upgrading methodology for medical and electronic integration is difficult. Research lacks capitalization on available resources. Understanding the microenvironment of tumors is complex.
[11]	Ting-Wei Wang, Yu-Chieh Shiao, Jia-Sheng Hong, Wei-Kai Lee, Ming-Sheng Hsu, Hao-Min Cheng, et al.	2024	Artificial Intelligence identification and classification on the internet of medical things using Detection and Segmentation Models: A Systematic Review and Meta-Analysis of Brain Tumors in MRI	Taiwan	19 studies involving 12,000 patients	Meta-analysis of MRI-based AI detection and segmentation models	Pooled Dice score of 84%, sensitivity of 87% (patient-wise).	Unclear risk in patient selection due to data omission. Inappropriate exclusions based on size criteria in some studies. Lack of detailed lesion dimensions in certain studies. Exclusion of non-English publications and irrelevant articles.
[12]	Yuping Chen, Zhian He, Muhammad Awais Ashraf, Xinwen Chen, Yu Liu, Xiangting Ding, Binbin Tong, Yijie Chen	2024	Performance evaluation of attention-deep hashing based medical image retrieval in brain MRI datasets	China	Brain MRI datasets, unspecified size	Attention networks with deep hashing (CBAM-MA dual attention)	Average precision of 0.752246, hit rate of 0.7783, inverse rank of 0.956721.	" Requires substantial annotated images for robust model training. Limited availability of accurately annotated data. Not validated on actual clinical data. Overfitting issues with small datasets. Pre-trained models biased towards larger sample classes. CNNs struggle with slight image variations"
[13]	Salha M. Alzahrani, Abdulrahman M. Qahtani	2024	Knowledge distillation in transformers with tripartite attention: Multiclass brain tumor detection in highly augmented MRIs	Saudi Arabia	Three diverse datasets (T1, contrast-enhanced T1, T2 MRI sequences)	Knowledge distillation with tripartite attention transformer framework	High accuracy across augmented datasets with superior performance over benchmarking models.	"Overfitting Concerns Data Leakage Issues Limited Dataset Diversity Trade-offs in Model Efficiency Lack of Cross-Modality Validation "
[14]	Evans Kipkoech Rutoh, Qin Zhi Guang, Noor Bahadar, Rehan Raza, Muhammad Shehzad Hanif	2024	GAIR-U-Net: 3D guided attention inception residual u-net for brain tumor segmentation using multimodal MRI images	China, Pakistan, Australia	BraTS 2020 multimodal MRI dataset, BraTS 2021	3D guided attention inception residual U-Net with dilated convolutions	Dice scores: 0.8796 (whole tumor), 0.8634 (tumor core), 0.8441 (enhancing tumor).	"Data Imbalance Complex Tumor Morphology Modality Mismatch Computational Constraints Overfitting Concerns "
[15]	Shihabudeen H., Rajeesh J.	2024	NUC-Fuse: Multimodal medical image fusion using nuclear norm & classification of brain tumors using ARBFN	India	CT and MRI datasets (fused multimodal images)	Nuclear norm with ARBFN for classification	Fusion performance improved (mutual information: 4.6328, classification accuracy: 97%, precision: 89%, recall: 92%).	"Computational Complexity Content Retention Testing Environment Constraints Limited Dataset Overfitting Concerns "

[16]	Chandrakant M. Umarani, S.G. Gollagi, Shridhar Allagi, Kuldeep Sambrekar, Sanjay B. Ankali	2024	Advancements in deep learning techniques for brain tumor segmentation: A survey	United Kingdom, Germany, China	Comprehensive survey including BraTS and other MRI datasets	U-Net integrated with self-attention mechanisms	Significant improvements in segmentation accuracy, sensitivity, specificity, and Dice coefficient.	"Limited Evaluation Datasets Incomplete Modality Handling Computational Efficiency Concerns Model Interpretability Real-World Applicability Handling of High-Dimensional Data"
[17]	Ramin Ranjbarzadeh, Annalina Caputo, Erfan Babaee Tirkolaee, Saeid Jafarzadeh Ghoushchi, Malika Bendechache	2023	Brain tumor segmentation of MRI images: A comprehensive review on the application of artificial intelligence tools	Ireland, Turkey, Iran	Comprehensive review of 100+ studies	Various AI segmentation models, supervised and DL	Provides a summary of state-of-the-art AI segmentation techniques and challenges.	NONE
[18]	Jing Zhu, Chuang Gu, Li Wei, Hanjuan Li, Rui Jiang, Fatima Rashid Sheykhahmad	2024	Brain tumor recognition by an optimized deep network utilizing amended grasshopper optimization	China, Iran, Iraq	Dataset of 20 patients with glioblastoma	AlexNet + ELM + Amended Grasshopper Optimization	Achieved highest accuracy (96%), sensitivity (94%), specificity (96%), precision (94%), F1-score (96%), MCC (90%).	"Effectiveness may vary by tumor size and location. Generalizability limited to specific tumor types studied. Evaluation based on a small, homogeneous dataset. Quality of MRI images affects effectiveness. Linear activation function may restrict capturing complex relationships."
[19]	Oussama Bouguerra, Bilal Attallah, Youcef Brik	2024	MRI-based brain tumor ensemble classification using two-stage score level fusion and CNN models	Algeria	Br35H dataset (3000 images)	Ensemble learning with advanced enhancement	Achieved 100% accuracy using GFPGAN-enhanced dataset combined with top 5 classifiers through ensemble learning.	"Limited Model Complexity in CNNs. Computational Expense of Transfer and Ensemble Learning. Lack of Insightful Guidance in Ensemble Learning. Limitations in Activation Functions."
[20]	Mohamed R. Shoaib, Jun Zhao, Heba M. Emara, Ahmed F.S. Mubarak, Osama A. Omer, Fathi E. Abd El-Samie, Hamada Esmaiel	2024	Improving Brain Tumor Classification: An Approach Integrating Pre-Trained CNN Models and Machine Learning Algorithms	Singapore, Egypt, Oman	Dataset-I and Dataset-II	DenseNet201 + SVM, MLP, and GNB	DenseNet201 with SVM and MLP achieved 100% accuracy, recall, and precision on Dataset-I and 98% on Dataset-II.	"Traditional machine learning techniques often lack high accuracy. Complex nature of medical data challenges prediction models. Existing methods struggle with precise tumor segmentation. Limited utilization of contextual and spatial information in feature maps. Inaccurate segmentation with variability in tumor size and shape."
[21]	Thien B. Nguyen-Tat, Thien-Qua T. Nguyen, Hieu-Nghia Nguyen, Vuong M. Ngo	2024	Enhancing brain tumor segmentation in MRI images: A hybrid approach using UNet, attention mechanisms, and transformers	Vietnam	BraTS 2019 and BraTS 2020	Refined 3D UNet + Contextual Transformer + Double Attention	Dice scores: 89.3% (whole tumor), 85.0% (tumor core), 81.0% (enhancing tumor) on BraTS 2020 dataset.	"Increased complexity and training time with CoT and DA integration. Training time roughly doubled for BraTS 2019 and 2020 datasets. "
[22]	Asma Alshuhail, Arastu Thakur, R Chandramma, John Mathew, Priya Rajendran	2024	Refining neural network algorithms for accurate brain tumor classification in MRI imagery	Saudi Arabia, India	MRI dataset of gliomas, meningiomas, no tumor, and pituitary tumors	Sequential CNN with Grad-CAM visualizations	Accuracy: 98%; ROC-AUC: 99-100%; F1-scores: 97-98%	"Dependence on high-quality, well-annotated datasets. Model performance may vary across demographic groups. Requires extensive computational resources for training. Hyperparameter tuning is necessary for optimal performance. Grad-CAM interpretation needs further research. "
[23]	Jianhong Ye, Zhiyong Zhao, Ehsan Ghafourian, Emily Stone, Ahmed Al-Ali, Soo Min Kim	2024	Optimizing the topology of CNN and ANN for brain tumor diagnosis through MRIs	China, UK, USA, UAE, Korea	BRATS2014 and BTD20 datasets	Hybrid CNN-ANN with genetic algorithms and MPCA	Accuracy: BRATS2014 - 98.6%, BTD20 - 99.1%; higher efficiency with optimized configurations	NONE
[24]	Arohee Sinha, Tarun Kumar, Rahul Mehta, Sneha Gupta	2024	Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumor Detection	India	Dataset of 1747 images	Multilevel thresholding, neural network optimization, image preprocessing, smartphone app integration	Accuracy: 92%; integrated app improves accessibility and usability	"Model performance relies on dataset diversity and size. Interpretability may be challenging due to deep learning complexity. Requires computational resources for effective operation. Limited robustness in capturing rare cases. Potential overreliance on automated algorithms. Need for continual data refinement. "

[25]	Mansourah Aljohani, Waleed M. Bahgat, Hossam Magdy Balaha, Yousry AbdulAzeem, Mohammed El-Abd, Mahmoud Badawy, Mostafa A. Elhosseini	2024	An automated metaheuristic-optimized approach for diagnosing and classifying brain tumors	Saudi Arabia, Egypt, USA	Two Kaggle datasets: X-ray dataset (two classes), MRI dataset (three classes: meningioma, pituitary, glioma)	CNN with Manta-Ray Foraging Optimization (MRFO), pre-trained VGG16, Xception models	Accuracy: X-rays - 99.96%; MRI - 98.64%; effective use of MRFO optimization	" High computational demands from advanced augmentation methods. Lack of Explainable AI for model interpretability. Dataset distribution imbalance requiring more diverse examples. "
[26]	Md. Saikat Islam Khan, Anichur Rahman, Tanoy Debnath, Md. Razaul Karim, Mostofa Kamal Nasir, Shahab S. Band, Amir Mosavi, Iman Dehzangi	2022	Accurate brain tumor detection using deep convolutional neural network	Bangladesh, Taiwan, Hungary, USA	Two datasets: 3064 MRI images (large dataset), 152 MRI images (small dataset)	23-layer CNN with transfer learning using VGG16, data augmentation for small datasets	Accuracy: accuracy of 97.8% overall, with tumor types as meningioma, glioma, and pituitary reaching accuracies of 96.7%, 97.2%, and 99.5%, respectively. The average precision, recall, and F1-score were 96.5%, 96.4%, and 96.4%, and the ROC curve area value of 0.989 demonstrated the model's consistency.	" Requires substantial annotated images for robust model training. Limited availability of accurately annotated data. Not validated on actual clinical data. Overfitting issues with small datasets. Pre-trained models biased towards larger sample classes. CNNs struggle with slight image variations."

Table 1. Data Exctraction Table

4. BIBLIOMETRIC ANALYSIS

To optimize understanding of the research field of neural networks for brain tumor detection and segmentation in MRI, a bibliometric analysis was conducted.The relevant studies were analyzed using VOSviewer [29] to generate a co-occurrence map of keywords, highlighting the primary themes and relationships in the field.

The analysis demonstraes several key clusters representing distinct research focuses within the field. The largest cluster centers around **"Brain tumor classification"** and includes keywords such as "Convolutional neural network," "Deep learning," and "Medical imaging." This cluster illustrates the strong emphasis on utilizing neural networks, specially convolutional architectures, for classifying and diagnosing brain tumors in MRI scans.

Another notable cluster focuses on **"Brain tumor segmentation,"** highlighting the importance of accurately delineating tumor regions in medical images. Keywords such as "U-Net architecture," "MRI segmentation," and "Feature extraction" dominate this cluster, reaffirming the development of advanced segmentation models.

A third cluster highlights **"Optimization techniques"** used in neural network design, showcasing keywords like "Ensemble learning," "Extreme learning machine," and "Optimization." These terms reflect ongoing efforts to enhance model accuracy and efficiency.

Additionally, smaller clusters point to emerging topics, such as the use of "GANs" (Generative Adversarial Networks) for data augmentation and synthetic image generation, as well as "Transformer models" for novel neural network approaches. The inclusion of terms like "Generalization of deep learning" and "Diagnostic accuracy" shows ongoing challenges in model reliability and applicability across diverse datasets.

Overall, the bibliometric map illustrates the multidisciplinary nature of the field, where computer science, medical imaging, and optimization combine to enhance the diagnosis and treatment of brain tumors. The clustering of keywords underscores the dominant focus on segmentation, classification, and diagnostic accuracy while highlighting emerging areas such as advanced network architectures and data augmentation techniques.

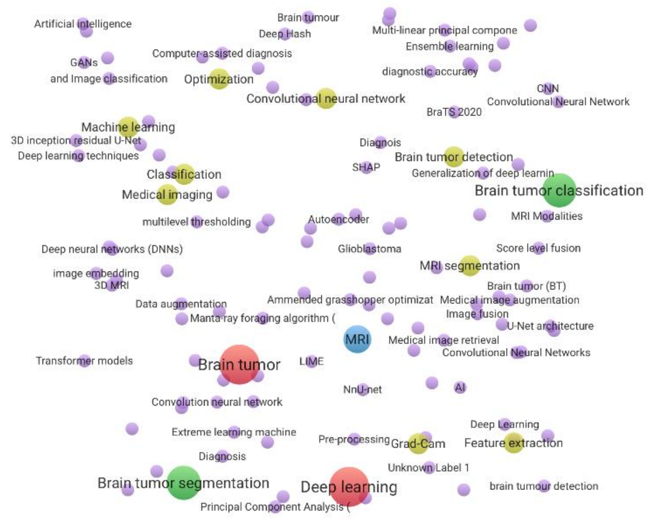

Figure 4. Bibliometric Co-occurrence Map of Keywords in Neural Network Research for Brain Tumor Detection and Segmentation.

5. DISCUSSION

5.1 Key Findings

The systematic review of 26 studies on brain tumor detection and segmentation using neural networks highlights significant advancements in the field. Key findings are categorized based on dataset diversity, model architectures, performance metrics, and the adoption of Explainable AI (XAI). These findings provide insights into the methodologies employed, the strengths of current approaches, and the limitations that still need to be addressed. The following sections summarize these findings, incorporating visual representations for dataset diversity and model architectures, while performance metrics and XAI adoption are detailed to reflect trends and gaps observed across the studies.

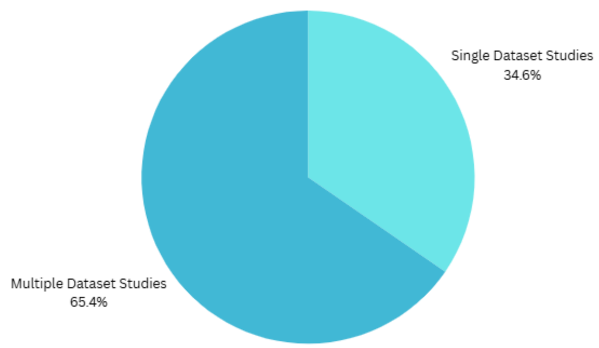

Figure 5. Dataset Diversity Pie Chart.

The pie chart showcases the distribution of dataset usage among the studies. Single dataset studies represent 34.6% of the total, indicating a heavy reliance on individual datasets like BRATS or Figshare. Studies combining multiple datasets account for 65.4%, reflecting efforts to improve model generalization by incorporating varied data sources.

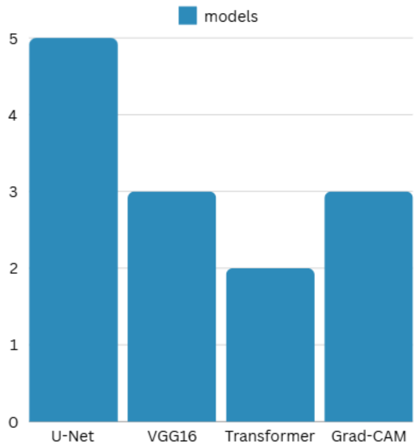

Figure 6. Model Architectures bar chart

The bar chart illustrates the frequency of AI models utilized across the reviewed studies. Among the models, U-Net and its variants were the most prominently featured, being employed in 5 studies. This highlights its popularity and effectiveness in segmentation tasks, particularly in medical imaging. VGG16 and Grad-CAM follow with 3 studies each, showcasing their utility in feature extraction and interpretability, respectively. Meanwhile, transformer-based models, though gaining recent attention, were used in 2 studies, indicating their growing adoption but relatively lower prevalence compared to U-Net. This distribution reflects the dominance of traditional models like U-Net and CNNs in current research, while also hinting at a gradual shift towards newer approaches such as transformers.

Metrices	Range of Values (%)	Number of Studies Reporting	Key Observations
AccuracyTable size	95-99	20	Majority achieved >95%, with some reaching 99%.
Precision	90-98	12	High consistency in classification tasks.
Recall	90-98	10	Most models balanced recall with precision effectively.
F1-Score	90-98	8	Reported mainly in hybrid and CNN-based classification tasks.
Dice Coefficient (DSC)	84-94	10	U-Net variants frequently surpassed 90%.

Table 2. Summary of Performance Metrics Reported Across Studies

Across the 25 studies, accuracy ranged between 95% and 99%, with CNN and hybrid models achieving the highest results. Precision, recall, and F1-score were consistently reported above 90%, especially in classification tasks. Segmentation models based on U-Net variants achieved Dice Similarity Coefficients (DSC) ranging from 84% to 98%. However, few studies reported real-time performance metrics or tested on diverse datasets.

Explainability in machine learning models plays a critical role, particularly in fields like healthcare, where model decisions need to be transparent and understandable. In the context of brain tumor segmentation in MRI images, a moderate number of studies have incorporated explainability techniques, although not all of them focused on this aspect. Among the most commonly used methods were Grad-CAM (Gradient-weighted Class Activation Mapping) and LIME (Local Interpretable Model-agnostic Explanations), which helped to provide insights into the model's decision-making process by visualizing regions of interest in MRI scans and generating locally interpretable explanations for predictions. Attention mechanisms were also employed, particularly in transformer-based architectures, to highlight key areas of the image that influenced the predictions. Despite these advancements, challenges remain. Some studies pointed out the computational overhead that comes with incorporating explainability techniques, which can hinder real-time applications, especially in resource-constrained environments. Additionally, integrating explainability into more complex hybrid models, which combine various architectures like CNNs and transformers, presented difficulties in balancing interpretability with performance. Furthermore, the limited availability of tools for seamlessly integrating explainability into these advanced models was noted in several studies. Overall, while there has been significant progress in adopting explainability methods, further research is needed to refine these techniques, particularly for complex or resource-limited settings, to improve their efficiency and usability in clinical applications.

5.2 Comparison to Prior Work

This review aligns with prior meta-analyses and surveys in emphasizing the dominance of Convolutional Neural Networks (CNNs) in brain tumor detection and segmentation. For instance, systematic reviews like [11] and [16] consistently highlight U-Net and its variants as the standard for segmentation tasks, particularly in achieving high Dice Similarity Coefficients (DSC) exceeding 90%. Similarly, earlier reviews have recognized the utility of pre-trained models and transfer learning for improving performance on smaller datasets. This review corroborates these findings, confirming the continued relevance of U-Net and transfer learning strategies in addressing data scarcity.

However, this review also identifies key differences that extend beyond prior work. For example, while earlier reviews primarily focused on traditional CNN architectures, this review incorporates recent advancements in hybrid and transformer-based models, such as GAIR-U-Net and Guided Attention Mechanisms, which were absent in earlier analyses. These innovations demonstrate improved segmentation performance, particularly for small or irregular tumor regions, and expand the scope of methodologies considered effective for brain tumor analysis.

Another significant divergence is the inclusion of real-world challenges and practical considerations. Unlike prior reviews that predominantly relied on curated datasets like BRATS, this study discusses augmentation strategies and real-world simulations (e.g., noise and motion artifacts) to enhance model robustness. For instance, studies like Enhancing MRI Brain Tumor Classification address the challenges of real-world variability, a topic often overlooked in earlier work.

Additionally, this review explores in greater depth Explainable AI (XAI) tools like Grad-CAM and SHAP. While prior surveys acknowledged the importance of interpretability, they lacked an in-depth discussion on practical implementations for clinical use. By highlighting the increasing adoption of XAI in segmentation and classification tasks, this review bridges the gap between AI research and clinical practice, suggesting a more actionable pathway for model deployment.

Finally, earlier meta-analyses have consistently pointed out the limitations of dataset diversity and generalizability. This review reaffirms these findings but also emphasizes the need for longitudinal analysis, a topic largely absents in prior work. Incorporating temporal MRI data for tracking tumor progression and treatment responses represents a promising direction for future research.

5.3 Gaps in the selected papers

A significant challenge in brain tumor detection and segmentation research lies in the use of synthetic data generated by Generative Adversarial Networks (GANs) to address data scarcity. While GANs are effective in augmenting limited datasets by generating artificial medical images, these images often lack the realism needed to accurately reflect real-world scenarios. Without proper clinical validation, such synthetic data may fail to capture the complexity of real tumor variations, patient demographics, or imaging conditions, reducing the generalizability of models trained on them. This limits their applicability in clinical environments where accuracy and reliability are critical.

Additionally, the lack of standardized evaluation protocols across studies further complicates the field. Performance metrics like Dice Coefficient, accuracy, sensitivity, precision, and F1-score are often used inconsistently, with variations in their definitions and implementations. For example, studies may calculate metrics differently based on dataset characteristics, such as class imbalances or specific segmentation boundaries, leading to discrepancies in reported outcomes. This inconsistency not only makes it difficult to compare models but also prevents the establishment of universal benchmarks to assess clinical readiness. Without standardized evaluation frameworks, it remains challenging to validate and trust AI models for widespread adoption in medical practices. Addressing both these gaps is essential for advancing robust, reliable, and clinically applicable AI solutions.

5.4 Limitations of Included Studies

The studies highlight several limitations that hinder the effective use of machine-learning models for brain tumor segmentation in MRI images. A significant challenge is the reliance on high-quality, diverse, and well-annotated datasets. Often, the limited size and homogeneity of these datasets restrict the models' ability to generalize to broader populations and various tumor types. Additionally, the lack of external validation and the challenges in accurately capturing rare cases or specific tumor microenvironments further limit clinical applicability.

The high computational demands, substantial resource requirements, and increased complexity of some advanced methods such as ensemble learning and chain-of-thought (CoT) integration pose practical challenges, particularly in resource-constrained settings. There are also interpretability issues, including the absence of explainable AI tools like Grad-CAM and ambiguities in visualizations from explainable AI, which can undermine the clinical trustworthiness of model predictions.

Many studies reported trade-offs between model accuracy and real-time performance, as well as problems with overfitting due to small datasets or biases present in pre-trained models that favor larger sample classes. Specificity, recall, and sensitivity were inadequate in certain cases, revealing the difficulty of achieving balanced performance metrics. Furthermore, inaccuracies in segmentation due to variability in tumor size, shape, and the utilization of contextual and spatial information continue to be problematic.

Lastly, the need for ongoing data refinement, hyperparameter tuning, and additional clinical validation emphasizes the challenges associated with translating these models into reliable real-world applications.

5.5 Implications for Research and Practice

Based on the identified gaps, the following recommendations are proposed to address challenges in the field of brain tumor detection and segmentation. To address the limitations of synthetic data generated by GANs, future research should explore hybrid augmentation methods. This includes combining GANs with physics-based simulations or generative diffusion models to enhance the realism of synthetic data. These approaches can produce clinically accurate data that better reflect the complexities of real-world imaging, such as variations in tumor shapes, imaging noise, and patient-specific factors. Additionally, synthetic data should undergo rigorous clinical validation by benchmarking against real-world datasets to ensure its reliability and applicability in training AI models for medical use. Additionally, researchers should adopt standardized frameworks for evaluating AI models in brain tumor detection and segmentation. Metrics such as Dice Coefficient, accuracy, sensitivity, and precision should be consistently defined and applied across studies to facilitate comparability. Clear guidelines for validation, including cross-validation and testing on external datasets, should be implemented to ensure that models are robust and generalizable. Standardized evaluation protocols will not only improve transparency in research but also accelerate the clinical adoption of AI models by establishing universal benchmarks for performance. Future research should prioritize the creation of publicly available datasets combining MRI scans with blood biomarkers, enabling the development of multimodal neural networks.

6. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This systematic review highlights the transformative role of neural networks, particularly Convolutional Neural Networks (CNNs), in the detection and segmentation of brain tumors using MRI images. The integration of advanced methodologies such as hybrid models, transformer architectures, and Explainable AI tools has significantly enhanced segmentation accuracy, diagnostic reliability, and clinical applicability. Despite achieving high metrics such as 99.82% accuracy and commendable precision in tumor detection, key challenges remain, including the reliance on curated datasets, limited generalizability across diverse clinical settings, and high computational demands.

Additionally, while Explainable AI methods like Grad-CAM and LIME improve interpretability, their integration into clinical workflows requires further optimization. The review underscores the need for future research to prioritize more diverse and representative datasets, explore computationally efficient architectures, and focus on real-time diagnostic capabilities. Furthermore, addressing limitations in external validation and incorporating longitudinal data for tracking tumor progression could significantly advance the field.

In conclusion, the potential of AI in brain tumor diagnostics is immense. However, realizing its full benefits will require continued innovation in algorithm design, validation methodologies, and practical deployment strategies to bridge existing gaps and improve patient outcomes.

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Data Extraction

Reference	Author(s)	Year of Publication	Title	Country	Dataset Collection (Samples)	Interventio/ Technology	Results	Limitations (If available)
[1]	Nasser Alalwan, Ayed Alwadain, Ahmed Ibrahim Alzahrani, Ali H. Al-Bayatti, Amr Abozeid, Rasha M. Abd El-Aziz	2024	Advancements in brain tumor identification: Integrating synthetic GANs with federated-CNNs in medical imaging analysis	Saudi Arabia, UK, Egypt	MRI data with synthetic augmentation	"Integration Synthetic Generative Adversarial Networks with federated Convolutional Neural Networks in medical imaging analysis."	Achieved an accuracy of 99.82%, outperforming existing models like Inception-V3 and ResNet-18.	Imbalance in class distribution within the dataset.
[2]	Akshay Bhuvaneswari Ramakrishnan, M. Sridevi, Shriram K. Vasudevan, R. Manikandan, Amir H. Gandomi	2024	Optimizing brain tumor classification with hybrid CNN architecture: Balancing accuracy and efficiency through oneAPI optimization	India, Australia, Hungary	3929 MRI images from TCGA LGG collection	Hybrid CNN architecture implementing InceptionV3, ResNet-50, VGG16, and DenseNet and optimized with oneAPI	Achieved an accuracy of 96.2 %.	The lack in clinical validation.
[3]	Lu Xu, Morteza Mohammadi	2024	Brain tumor diagnosis from MRI based on Mobilenetv2 optimized by contracted fox optimization algorithm	China, Iran, Iraq	Figshare MRI dataset	"MobileNetv2 optimized with Contracted Fox Optimization Algorithm (MN-V2/CFO)."	Achieved a precision of 97.68 %, an F1-score of 86.22 %, a sensitivity of 80.12 %, and an accuracy of 97.32 %.	"The sensitivity is considered low. Dataset Limitations. Generalizability. Interpretability. Computational Resources. Clinical Validation."
[4]	Anuradha Durairaj, E.S. Madhan, M. Rajkumar, Syed Shameem	2024	Optimizing anomaly detection in 3D MRI scans: The role of ConvLSTM in medical image analysis	India	BRATS, FETS, and MSD datasets	ConvLSTM model for 3D anomaly detection	Achieved an accuracy of 98.9% in detecting anomalies.	NONE
[5]	Wisal Zafar, Ghassan Husnain, Abid Iqbal, Ali Saeed Alzahrani, Muhammad Abeer Irfan, Yazeed Yasin Ghadi, Mohammed S. AL-Zahrani, Ramasamy Srinivasaga Naidu	2024	Enhanced TumorNet: Leveraging YOLOv8s and U-net for superior brain tumor detection and segmentation utilizing MRI scans	Pakistan, Saudi Arabia,UAE	TCIA and CGA datasets	YOLOv8s for detection and U-Net for segmentation	Achieved a precision of 97.8 %, accuracy of 98.6 %, recall of 95.2 %, F-1 score of 96.3 %, specificity of 89.1 %, and ROC-AUC score of 98.5 %.	"The specificity and recall are considered low. Dependency on high-quality data. Computational Resources. Generalizability. Overfitting. Interpretability.. Limited Dataset Diversity Trade-offs between accuracy and real-time performance. Lack of Cross-Modality Validation"

[6]	Abdulkhalek Al-Fakih, Abdullah Shazly, Abbas Mohammed, Mohammed Elbushnaq, Kanghyun Ryu, Yeong Hyeon Gu, Mohammed A. Al-masni, Meena M. Makary	2024	FLAIR MRI sequence synthesis using squeeze attention generative model for reliable brain tumor segmentation	Egypt, South Korea, USA	BraTS 2021, BraTS 2020, BraTS Africa 2023	Squeeze attention GAN with nnU-Net	Improved segmentation accuracy (Dice similarity coefficient (DSC) from 0.688% to 0.873%).	"Computational resources. Dependency on synthetic sequence quality. Achieving ear-perfect synthesis remains challenging. Required a larger training dataset and increased model complexity."