Deep Learning Approaches for Brain Tumor Detection in MRI Images: Recent Advances, Challenges, and Future Research Directions

T. Lakshmi Narayana[1,2], Ahmed Alemran[3]

[1]Post-Doctoral Researcher, Lincoln University College, 47301, Petaling Jaya, Selangor Darul Ehsan, Malaysia

[2]Associate Professor, Department of Electronics and Communication Engineering, KLM College of Engineering for Women, Kadapa, Andhra Pradesh, India – 516005

[3]Department of Software Engineering, Medicine College, Misan University, Amarah, Iraq

Email ID: [1,2] lakshmi.svuniversity@gmail.com ; [1,2] lak.svuce@gmail.com ; [3] ahmed.mcm@uomisan.edu.iq

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Abstract: Brain tumors are serious disorders of the brain and require early and precise diagnosis for proper treatment. MRI is the imaging modality of choice as it provides excellent soft tissue contrast, and doesn't involve any type of radiation. In recent years, deep learning techniques such as CNN, U-Net, Vision Transformers, hybrid architectures and attention-based models have contributed to the advancement of automated brain tumor detection, segmentation, and classification. This review gives an overview of the recent deep learning methods, including image pre-processing, feature extraction methods, segmentation methods, classification methods, benchmark datasets, and evaluation metrics. It also covers the main problems encountered in clinical use, including a lack of annotated datasets, class imbalance, lack of model generalizability, computational cost, interpretability, and deployment. Lastly, future research trends are emphasized such as self-supervised learning, explainable AI, federated learning, multimodal learning, lightweight architectures, and foundation models. This review will be valuable for suggesting directions for future research and development that could lead to more accurate, efficient, and clinically usable deep learning applications in the diagnosis of brain tumors.

Keywords: Brain Tumor; Detection; MRI; Deep Learning; Medical Image Analysis; Computer-Aided Diagnosis

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Introduction

Brain tumors are among the most serious neurological disorders and if diagnosed late can cause serious health issues and reduce life expectancy. They are formed as the abnormal growth of cells in the brain or in the tissues around it and are generally classified as primary tumor (developing in the brain) or secondary tumor (formed when cancer occurs elsewhere in the body and spreads to the brain). Gliomas, especially glioblastoma multiforme (GBM), are among these that are highly aggressive and have poor prognosis. Thus, prompt and reliable diagnosis of brain tumors is of crucial importance for successful management and treatment [1]. Magnetic Resonance Imaging (MRI) is the most common imaging method used for the diagnosis of brain tumors, as it offers excellent tissue contrast, eliminating the need to use ionizing radiation [2]. Various types of MRI sequences are used to obtain complementary information that aids in the identification of the location, extent, tumor edema and characteristics of the surrounding tissues. These include T1-w, T1_CE, T2-w and FLAIR. Although there are many benefits, manual MRI interpretation is still a difficult and time-consuming process because of the vast and variable characteristics of tumors and the need for expert radiological assessment [3].

CAD systems have been developed to automate brain tumor] analysis in order to support the clinical diagnosis. Most early CAD methods were based on conventional ML that needed to be taught handcrafted features describing image texture, shape and intensity. These approaches yielded promising outcomes, but they were sometimes less effective in handling more intricate and heterogeneous clinical data sets due to the fact that manually engineered features failed to capture the diversity of brain tumor data [4]. In recent years, DL has revolutionized medical image analysis by allowing the automatic extraction of many features directly from MRI data. CNNs have been adopted in numerous brain tumor detection and classification systems as they are able to learn complex image representations. AlexNet, VGG, ResNet, DenseNet and U-Net architectures have made outstanding advancements in diagnostic performance. All these advancements have largely contributed to the reliability of the automated brain tumor diagnosis and are still inspiring research in creating more reliable and clinically usable intelligent healthcare systems. The pipeline combines state-of-the-art (SOTA) deep learning (DL) methods with recent developments like transformer architectures, explainable AI and federated learning, offering a complete conceptual backbone for brain tumor automatic diagnosis.

Motivation and Problem Statement

Although deep learning has made great contributions, there are still some problems that hinder the application of DL in brain tumor diagnosis in clinical practice. High performance of most DL models depends on large MRI datasets that are well annotated. Producing these datasets, however, is challenging due to the time and clinical expertise that is needed to annotate medical images, and the amount of resources required. Furthermore, model performance is frequently different depending on the MR scanner, imaging protocol and patient population, and can be challenging to generalize to other hospitals. Several ways to address these limitations have been introduced. To reduce the reliance on manually labeled data, self-supervised learning can be used to learn meaningful features from large numbers of unlabeled MRI images. The federated learning and XAI aims to increase transparency in the prediction of models by offering visual explanations that help the physician to understand the decision-making process. Furthermore, multimodal learning integrates the data from multiple MRI sequences and clinical information, enabling more accurate diagnosis, and lightweight deep learning models minimize the computational burden and facilitate deployment on resource-limited clinical and edge devices. There are several review articles that explore DL applications in brain tumor analysis, but most of them are dedicated to particular applications like segmentation or classification. In the last few years, this research area has grown significantly with the rise of transformer-based architectures, attention mechanisms, self-supervised learning, federated learning, explainable AI, and foundation models, necessitating a timely and extensive review of this research.

This review gives a detailed survey of the latest DL techniques for brain tumor recognition from MRI. It covers all the steps in the image analysis pipeline, such as image preprocessing, feature extraction, tumor segmentation, classification, publicly available datasets, and evaluation metrics. The review also critically evaluates the strengths and weaknesses of the current methods, areas of current research gaps, and future research directions.

This review brings together recent advances on a single platform, to help researchers, clinicians and healthcare professionals build accurate, efficient, interpretable and clinically relevant deep learning solutions for brain tumor diagnosis.

Related works

The analysis of brain tumors from MRI images has benefitted greatly from recent progress in the field of artificial intelligence. Tumor detection, segmentation, classification and grading has been improved by incorporating the deep learning algorithms such as CNN, transfer learning, hybrid models, and transformer-based models that learn meaningful features from images. These methods have shown satisfactory results but there are some remaining issues that need more investigation including limited annotated data, model generalization, interpretation, computational resource, and real-time clinical use.

Guan et al. (2026) introduced a hybrid deep learning network, ResSGA-Net, which combines ResNet50, dual attention mechanisms, and a Swin Transformer for MRI-based brain tumor classification. Feature fusion and attention-based learning proved effective and the model achieved a high accuracy of more than 98%. The hybrid architecture of ResSGA-Net makes it high in computational complexity, memory consumption and inference time despite the high accuracy. It also lacks optimization for lightweight use, edge deployment and resource-limited healthcare settings 5]. Shivahare et al. (2026) introduced a semi-supervised learning approach integrated with multi-scale CNNs and Transformer based attention for detecting and classifying brain tumors in MRI images with MultiAttenNet, a hybrid deep learning framework. The framework is useful for local and global features and minimizes relying on a large labeled dataset. It was tested on the BraTS 2023 and Figshare Brain Tumor datasets, and it has been shown to achieve an accuracy of 98.4%, sensitivity of 96.8%, and specificity of 99.2%, better than some of the existing methods. MultiAttenNet has high diagnostic performance, but with a hybrid architecture, it introduces computational complexity, high memory requirements, and long inference time. The framework is also not light, offers no explainable AI or edge deployment, which makes it less suitable for real-time and resource-constrained clinical settings. These constraints underscore the importance of practical, interpretable and efficient deep learning models for healthcare applications [6].

Ishfaq et al. (2025) suggested a smart deep learning framework for brain tumor detection and classification based on a custom CNN, Inception-v4 and EfficientNet-B4. The system was able to perform well with an accuracy of 99.76% on EfficientNet-B4, 99.56% on Inception-v4, and 97.58% on the custom CNN for MRI images classified into 10 different classes of brain tumors. The framework could also be used for smart healthcare applications, as it remained effective in terms of prediction accuracy after deployment. It relies on high computational cost pre-trained models and limits clinical settings. It is also not built using a transformer-based feature learning, lightweight optimization, explainable AI or edge deployment strategies. These constraints emphasize the importance of effective, communicable and edge-compatible deep learning models for real-time brain tumor diagnosis [7]. Disci et al. (2025) compared the performance of a set of transfer learning pretrained CNN models: Xception, MobileNetV2, InceptionV3, ResNet50, VGG16 and DenseNet121 to perform a multi-class classification of brain tumors based on a dataset of 7,023 MRI images. In comparison, Xception achieved the highest performance in the weighted accuracy on the brain tumor dataset with 98.73% and the highest weighted F1 score of 95.29%, highlighting the effectiveness of transfer learning for brain tumor diagnosis. While the idea is able to obtain high classification accuracy with reduced training effort, it is limited to pre-trained CNN models and does not make use of transformer-based feature learning, optimizing the model, explainable AI, or edge deployment techniques. Furthermore, the inferior recall of some tumor classes suggests that better, more explainable, and lesser complex models are needed for in vivo tumor characterization [8]. The hybrid model proposed by Agarwal et al. (2024) involves combining Optimal Discrete Transform Weighted Contrast Histogram Equalization (ODTWCHE) with transfer learning using InceptionV3 for brain tumor classification from MRI images. The contrast enhancement technique has enhanced the image quality prior to classification, which in turn helped to extract features. The proposed method outperforms the following well-known CNN models such as AlexNet, VGG16, VGG19, DenseNet201, GoogLeNet, ResNet50 with classification accuracy of 98.89%. The framework was able to successfully enhance the images and transfer the classification model but it is based on an expensive deep learning model. Moreover, it fails to consider lightweight architecture design, explainable AI, and edge deployment, restricting its use for real-time and resource-constrained clinical contexts. The encountered restrictions emphasize the necessity of effective, yet interpretable and deployable deep learning frameworks for real-world applications in brain tumor diagnosis [9].

Gupta et al. (2024) suggested an automated brain tumor detection system using a three-layer CNN and MRI images. The model has learned the hierarchical image features automatically with no manual feature extraction and a precision of 90%. It has a shallow architecture which is less computationally complex compared to deeper CNN models. The proposed CNN is computationally efficient, but its performance in detecting is lower than the recent hybrid models and the transformer model. Also, it has no attention mechanism, explainable AI, light-weight optimization, and edge deployment that could help improve accurate and real-time clinical diagnosis. These constraints underscore the need for lightweight, interpretable and edge-compatible deep learning frameworks for brain tumor detection [10].

Research Gaps and Future Research Needs are identified.

While deep learning has made great strides in detecting and classifying brain tumors from MRI images, there are still several challenges that hinder its use in clinical practice. One of the primary challenges for developing robust and generalizable models is a lack of size, diversity, and annotation for MRI datasets. Moreover, in order to make a classification, class imbalance and a limited number of rare tumor samples have a negative impact on the classification accuracy. One of the significant hurdles is the computational complexity of sophisticated deep learning models, hindering their application in resource-limited or real-time settings. Very few studies at present have been validated with clinical data, and the majority of current studies are based on the benchmark data, limiting the practical reliability of the studies. As a result, although many models have been well tested in the lab, only a few can be translated into successful clinical practice. Thus, the recent progress on CNNs, transformer-based networks, hybrid architectures, self-supervised learning, explainable AI and federated learning have significantly improved the analysis of brain tumors.

Proposed Methodology

The proposed framework as shown in figure 1 is aims to give an efficient and light weight approach to automatic brain tumor classification using MRI images. First the image pre-processing, in which the MRI images are resized, denoised, normalized and contrast enhanced to improve the image quality and to have a consistent input for subsequent image analysis. Then an Attention U-Net model is applied to precisely localize and segment the tumor area in the MRI images. The segmented region is then fed into the proposed LiteEdgeSONet (Lightweight Edge-Optimized Self-Optimizing Network), which is capable of extracting meaningful and useful features and classification of tumor with low computational complexity.

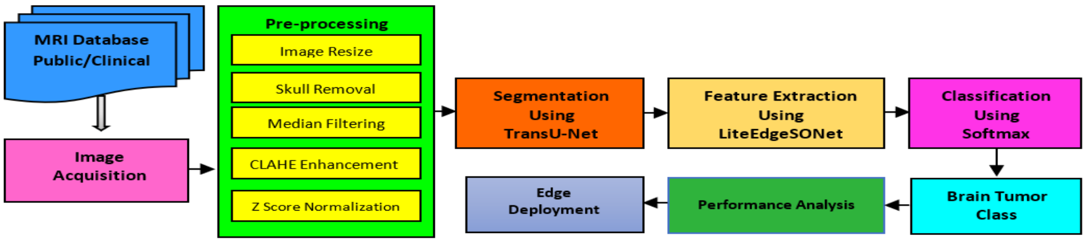

Figure 1. Lightweight Deep Learning Based Proposed Framework.

Finally, a Softmax layer classifies the MRI image to the correct tumour class. The proposed model is lightweight and has an optimized architecture, which makes it suitable for deployment on cloud platforms, workstations, and edge computing devices, thus making it an appropriate solution for real-time computer-aided brain tumor diagnosis.

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