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Deep Learning Approaches to Brain tumor Detection: A Review

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Abstract: Brain tumors are a major global health challenge and one of the leading causes of death worldwide. Early detection is critical to improving survival. However, obtaining reliable and accurate results remains a significant challenge, even when utilizing high-quality brain imaging techniques. Diagnosing a brain tumor is often a lengthy process that requires extensive radiological expertise. In this context, using deep learning, particularly convolutional neural networks (CNNs), is a promising approach for improving both the accuracy and the efficiency of the diagnosis of brain tumors. This review analyses studies published between 2020 and 2024 on deep learning techniques to identify and categorize brain tumors. It also highlights the variety of methodologies and algorithms that have been put forth and evaluates the diverse applications of deep learning. In addition to publicly available datasets, it examines radiological imaging techniques. The aim of this study is to evaluate the effectiveness of different deep learning models in the identification and categorization of brain tumors from medical scans. Furthermore, the review highlights notable advances in the field and underscores crucial gaps.

Keywords: medical imaging, brain tumor detection, convolutional neural networks, deep learning.

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1. **Introduction**

Brain tumors are a major global health problem, accounting for more than 300,000 cases each year, according to the World Health Organization (WHO). They have increasing incidence rates worldwide (Arulmani et al., 2024). This makes early diagnosis a necessity to prevent their prevalence. Machine learning and deep learning can help diagnose and prevent brain tumors. Deep learning algorithms are the most preferred due to their high performance.

Brain tumors can be divided into two main categories (Arulmani et al., 2024): primary tumors, formed in the brain, and metastatic tumors, originating in other parts of the body and four times more frequent. Primary tumors are either glial or non-glial, benign or malignant. The WHO has classified tumors into 4 grades according to their malignancy, growth and histological characteristics. Grade 1 tumors are benign, growing slowly and often treatable by surgery. Grade 2 tumors, though benign, may involve neighboring tissues and recur at a higher grade. Grade 3 tumors, which are malignant, propagate rapidly and require treatments such as chemotherapy. Grade 4 tumors, the most aggressive, spread rapidly, recur frequently and require combined therapies.

Brain tumors can be classified according to how they grade, as follows (Kim and Lee, 2022): Craniopharyngiomas, which are benign but difficult to remove because of their proximity to critical structures such as the pituitary gland, are a type of low-grade brain tumor (grades I and II). Chordomas, rare malignancies, typically affect the axial bones and require targeted radiation therapies such as carbon ion or proton therapy. Gangliogliomas and gangliocytomas, often associated with seizures, develop in the temporal lobes and are common in young adults. Schwannomas, benign tumors of the peripheral nerves, are often treated with surgery or radiation, although vestibular schwannomas can cause hearing loss. Pituitary adenomas and pineocytomas, which are usually benign, occur in the pituitary gland and pineal gland, respectively, and are generally slow growing and treatable. High-grade (grade III and IV) brain tumors include anaplastic astrocytomas, aggressive malignancies that require surgery, radiation therapy, and chemotherapy. Anaplastic oligodendrogliomas, which originate from myelin-producing cells, also require a multimodal approach. Glioblastoma multiforme (GBM), the most malignant and aggressive form, is distinguished by abnormal cells, necrotic areas, and new blood vessel formation. There is no standard treatment for recurrent cases, but treatment typically includes surgery, radiation and chemotherapy.

The World Health Organization (WHO) classified malignant brain tumors as destructive and fatal neoplasms with high mortality rates that affect all age groups (Xie et al., 2022). According to the WHO, 9.6 million people worldwide die from brain tumors each year. Brain tumors are a common and serious disease that significantly reduces the life expectancy of people of all genders and all age groups (Buabeng et al., 2024). Early detection and treatment are critical to prevent permanent organ damage.

In the field of medical decision support, artificial intelligence (AI) is increasingly being used for disease detection and accurate diagnosis, has made remarkable progress in recent years. Solving real-world problems in different fields. Deep learning (DL), a branch of AI, is rapidly revolutionizing several fields by successfully tackling complex challenges like natural language processing and image recognition. Its powerful capabilities have also been applied to medicine, where DL models have proven effective in a variety of applications.

This paper is structured as follows: Section 2 presents an overview of machine learning and deep learning techniques used for brain tumor classification and detection. Section 3 discusses different imaging modalities, datasets and selection criteria considered in this review. Section 4 provides a performance analysis, while Section 5 concludes the study.

2. Literature review of brain tumor classification models

A wide range of machine learning and deep learning methods have been developed for brain tumor image classification. In (Prabha and Singh, 2024), the authors used the EfficientNet family to automatically detect and classify three types of brain tumors using magnetic resonance imaging (MRI). Their study demonstrated the effectiveness of these architectures, achieving the following accuracy rates 96.07% (EfficientNet-B0), 97.86% (EfficientNet-B1), 98.21% (EfficientNet-B2), 97.86% (EfficientNet-B3), 98.93% (EfficientNet-B4), 99.64% (EfficientNet-B5), 98.57% (EfficientNet-B6) and 99.64% (EfficientNet-B7).

In (Tiwari et al., 2025), Raj Gaurang Tiwari et al. introduced the Adaptive Neuro-Fuzzy Inference System-Fusion-Deep Belief Network (ANFIS-F-DBN) model, which achieved an accuracy of 90.00%. In [13], the authors propose an automatic brain tumor diagnosis system that uses a convolutional neural network (CNN) for both classification and segmentation of glioblastomas. Using 1,800 images from the BraTS 2017 dataset, their model achieved a maximum accuracy of 99%.

The study in (Ahmed et al., 2024) introduced a hybrid ViT-GRU model, where the Vision Transformer (ViT) extracts essential features and the Gated Recurrent Unit (GRU) identifies relationships between them. This approach effectively addresses class imbalance and outperforms existing diagnostic methods. The model was trained using multiple optimizers, including SGD, Adam and AdamW, and evaluated through rigorous 10-fold cross-validation. In addition, Explainable Artificial Intelligence (XAI) techniques – such as Attention Maps, SHAP and LIME – were integrated to improve interpretability. On the primary data set, BrTMHD-2023, the model achieved its highest accuracies with different optimisers: 81.66% (SGD), 96.56% (Adam) and 98.97% (AdamW). In (Alshuhail et al., 2024), the authors developed a deep learning based model using convolutional neural networks (CNNs). The proposed model follows a sequential CNN architecture with multiple convolutional, max-pooling and dropout layers followed by dense layers. This model achieved an overall test accuracy of 98%, demonstrating a significant improvement in diagnostic accuracy.

Suganya Athisayamani et al (Alshuhail et al., 2025) used the AlexNet50 deep model for classification using a discriminative learning method. Their approach consists of three learning stages: (1) feature learning using the entire dataset, (2) training on an extended dataset while freezing certain AlexNet50 layers, and (3) further training on the extended dataset while leaving the frozen layers unchanged. The method was tested on three publicly available MRI classification datasets. Several hyperparameter optimisation techniques – including Adam, Stochastic Gradient Descent (SGD), Root Mean Square Propagation (RMSprop), Adamax and AdamW – were used to evaluate the learning process. The highest classification performance was achieved on the HWBA dataset with an average accuracy of 98%.

In 2024, researchers have proposed a novel MRI-based brain tumor detection method that integrates machine learning and deep learning techniques. MRI images were pre-processed using a median filter combined with an adaptive contrast enhancement algorithm (ACEA) to improve image quality and reduce noise. Segmentation was performed using a fuzzy c-means algorithm. Feature extraction was based on the grey level co-occurrence matrix (GLCM), including energy, mean, entropy and contrast. Classification was performed using the Ensemble Deep Neural Support Vector Machine (EDN-SVM), which combines deep neural networks with SVMs. The model achieved 97.93% accuracy in distinguishing between normal and abnormal brain tissue in MRI scans (Anantharajan et al., 2024). Zelenak and collaborators have introduced the Brain Tumor Recognition using an Equilibrium Optimizer with a Deep Learning Approach (BTR-EODLA) technique for MRI image analysis. This method is designed for high accuracy brain tumor detection. The BTR-EODLA approach applies median filtering (MF) to reduce noise in MRI scans, uses the squeeze-excitation ResNet (SE-ResNet50) model for feature extraction, and uses the Equilibrium Optimizer (EO) to fine-tune model parameters. A Stacked Autoencoder (SAE) is then used for tumor detection. Experimental results showed an impressive accuracy of 98.78%, confirming the effectiveness of the proposed technique (Zelenak et al., 2013).

3. Méthodologie

In this section, we present the criteria taken into account when selecting the papers chosen in the present work, as well as different brain tumor detection datasets and medical imaging techniques.

3.1. Selection criteria

The articles selected for this paper were searched using databases known for their coverage of medical and deep learning related scientific publications. Specifically, we used PubMed, Google Scholar and Scopus, which highlights the most recent and relevant research in medical imaging and artificial intelligence. It includes only studies published between 2021 and 2025 that focus on leveraging deep learning techniques for brain tumor detection and classification. Inclusion criteria were strictly defined and included papers that applied deep learning models to medical images, including MRI and PET scans.

3.2. Medical imaging techniques and datasets

3.2.1. Medical imaging techniques

A number of conventional methods have been used in the past for brain tumor imaging (Zelenak et al., 2013), these include non-invasive and invasive imaging modalities such as x-rays, ultrasound, computed tomography (CT) and magnetic resonance imaging (MRI). While X-rays played a pivotal role in their early use, their low sensitivity led to the subsequent emergence of more advanced techniques, such as CT and MRI. Ultrasound continues to find application in real-time intraoperative monitoring, but its use has been largely supplanted by MRI-based neuronavigation. The use of CT is effective in the detection of bone abnormalities and provides rapid imaging; furthermore, advanced techniques such as CT angiography and perfusion imaging are now well established. MRI is considered the gold standard in brain imaging; its unparalleled tissue contrast and detailed imaging make it ideal for tumor assessment. However, it should be noted that CT is more widespread and affordable than MRI.

- **Datasets**

Researchers have used several MRI datasets for brain tumor classification. These include the Brain Tumor Dataset (from Figshare or collected by the authors), the BRATS Dataset (especially BRATS2015), and datasets available on Kaggle. These databases typically include classes such as meningioma, glioma, pituitary, or tumor/non-tumor. MRI scans are often pre-processed (e.g. resized, normalized, noise suppressed) before analysis. Researchers can collect data directly or get it from public databases (like Figshare) and use it to classify images into categories of binary (tumor/non-tumor) or multi-class (specific tumor types). Table 1 summarizes the dataset types used in the studies included in this review.

Table 1. datasets used in brain tumor classification.

Dataset	Source	Classes
Brain Tumor Dataset	Figshare, Collected by authors	Meningioma, Glioma, Pituitary, Tumor / Non-Tumor
BRATS Dataset	BRATS2015	High Grade Glioma, Low Grade Glioma

Figshare Dataset	Figshare	Meningioma, Glioma, Pituitary, Tumor / Non-Tumor
Kaggle Dataset	Kaggle	Cancerous, non-cancerous
MRI Images Collected	By authors	Glioma, Meningioma, Pituitary, Tumor / Non-Tumor
Brain MRI Images	Various sources	Tumor / non-tumor

4. **Performance analysis**

Several methods stand out for their high accuracy, among the most effective approaches for brain tumor classification. The EfficientNet family (Prabha and Singh, 2024), using the EfficientNet-B5 and B7 architectures, reached a maximum accuracy of 99.64%, demonstrating the effectiveness of these models in MRI image analysis. The hybrid ViT-GRU model (Ahmed et al., 2024) achieved outstanding results, reaching an accuracy of 98.97% through the integration of explicable AI techniques and hyper-parameter optimization. Using classical architectures, AlexNet50 (Alshuhail et al., 2025) and a sequential CNN model (Alshuhail et al., 2024) both achieved 98.00% accuracy. Another promising method, the BTR-EODLA model (Zelenak et al., 2013), achieved an impressive 98.78% by combining preprocessing, features extraction and parameter optimization.

Table 2. Performance comparison of the reviewed models (Annex).

Reference Number	**Method**	**Accuracy (%)**
(Prabha and Singh, 2024)	EfficientNet-B5/B7	99.64
(Ahmed et al., 2024)	Hybrid ViT-GRU	98.97
(Alshuhail et al., 2024)	Sequential CNN	98.00
(Alshuhail et al., 2025)	AlexNet50	98.00
(Zelenak et al., 2013)	BTR-EODLA	98.78

5. **Conclusion**

A brain tumor is an irregular growth of brain tissue that interferes with the normal functioning of the brain. The primary objective of medical imaging is to develop algorithms capable of extracting accurate and relevant information while minimizing errors. The classification of brain tumors using MRI data is generally divided into four main steps: pre-processing, image segmentation, feature extraction, and tumor classification. However, achieving a fully autonomous system for clinical applications remains challenging due to the variable appearance, irregular size, shape and nature of tumors. This study aims to provide an overview of recent developments in brain tumor research, highlighting imaging techniques, summarising the WHO tumor classification standards and examining the deep learning algorithms applied to brain tumor classification. Compared to region growing methods and traditional machine learning approaches, deep learning techniques offer notable advantages in automated detection and classification of brain tumors, mainly due to their powerful feature learning capabilities. Although the contribution of DL techniques has been significant, the need for a general technique is still an issue.

ANNEX

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