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Review of Deep Learning Algorithms for Brain Tumor Classification: An Overview

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Abstract

The classification of brain tumors using deep learning algorithms has emerged as a crucial area of research in medical image analysis. This review provides a comprehensive overview of the application of deep learning techniques in the field of brain tumor classification. Deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable performance in accurately diagnosing brain tumors from medical imaging data, including MRI and CT scans. This review synthesizes the key findings from recent studies, highlighting the advancements in model architectures, data preprocessing, and performance evaluation metrics. The paper also discusses the challenges and limitations faced by these algorithms, such as the scarcity of labeled data, model interpretability, and generalization to diverse patient populations. Furthermore, it explores potential future directions in the field, including the integration of multi-modal data and the incorporation of explainable AI techniques to enhance clinical adoption. Overall, this review serves as a valuable resource for researchers, clinicians, and policymakers interested in the intersection of deep learning and brain tumor classification, offering insights into the current state-of-the-art and avenues for future research.

Introduction

The classification of brain tumors is a critical task in the realm of medical diagnostics, with profound implications for patient treatment and prognosis. Traditionally, this task has relied on the expertise of radiologists to interpret medical imaging data, such as magnetic resonance imaging (MRI) and computed tomography (CT) scans. However, with the rapid advancements in deep learning techniques, there has been a paradigm shift in how brain tumors are diagnosed.

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Deep learning algorithms, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have emerged as powerful tools for automating the process of brain tumor classification, offering the potential for faster and more accurate diagnoses. This review aims to provide a comprehensive overview of the application of deep learning algorithms in the domain of brain tumor classification. It is imperative to recognize that the successful utilization of deep learning in medical image analysis has the potential to revolutionize healthcare by improving diagnostic accuracy and reducing the burden on healthcare professionals. The motivation behind this review lies in the remarkable progress made in recent years, which has seen deep learning algorithms consistently outperform traditional methods in various medical imaging tasks, including brain tumor classification. Deep learning models have the capacity to extract intricate patterns and features from complex medical images, enabling them to differentiate between benign and malignant tumors with an unprecedented level of accuracy. Throughout this review, we will explore the key components that constitute the landscape of deep learning algorithms for brain tumor classification. This will encompass an examination of different model architectures, data preprocessing techniques, and performance evaluation metrics that have been employed in recent research. We will delve into the strengths and weaknesses of these algorithms, addressing challenges such as the scarcity of labeled data, model interpretability, and their ability to generalize across diverse patient populations.

MAGNETIC RESONANCE IMAGING

Using magnetic resonance The imaging approach makes use of computer-generated radio waves in-depth information and images of diverse biological organs and structures. Because MRI participants are not exposed to dangerous radiation like CT scans are, it is fully safe for use on people. It is beneficial because it provides a cross-sectional image of the brain that can be examined.

Most MRI devices have a tube-like design with a magnetic field surrounding them. To do the examination, the patient must lie down on a table that glides into the tube-shaped machine. In most cases, the body's water molecules are randomly arranged. MRI functions because the magnetic field causes the protons in hydrogen atoms to align. These atoms' protons start to spin in a particular direction after being exposed to a radio wave beam, releasing faint signals that the MRI machine may pick up.

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For subsequent examination, these signals are transformed into MRI pictures [12]. Cross-sectional pictures of the brain can be produced using this method. These images can be used to identify the tumor, analyze its size and shape, and choose the most effective course of treatment for the brain tumor.

MR imaging features of a brain tumor

MRI is a more beneficial imaging method than X-rays [9]. The information provided by MR images is sufficient for medical professionals to diagnose diseases and make decisions without the use of dangerous radiation. Brain tumor identification and diagnosis require pre-processed MR images. Depending on the need, various MRI types are employed in this operation. Sequences like T1, T2, and FLAIR that are commonly employed in MRI are provided as input during the preprocessing stage.

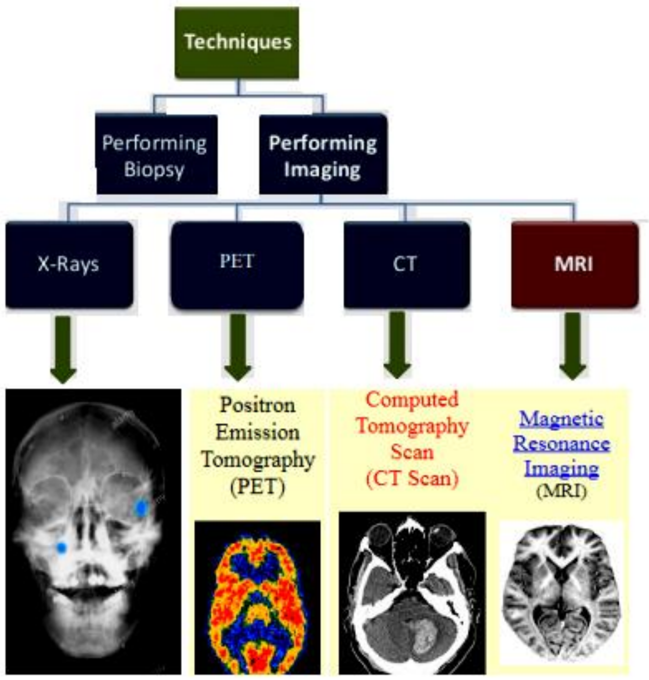

FIGURE 1 Different technique of Brain tumor imaging

Understanding the TE and TR principles is necessary in order to comprehend the different MRI image formats. TE is the amount of time (time of echo) that passes between an RF pulse being transmitted and an echo signal being received. The repetition period, or TR, is the amount of time that passes between two successive continuous pulses.

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T1-weighted imaging [11]: CSF and fluid have a black hue. White matter (WM) is lighter than grey matter (GM) When it comes to photographs of the brain's architecture, T1 produces superior results since fat is more visible. The pictures are produced with a short TE and TR time (TR is 500msec, TE is14msec) using longitudinal relaxation.

T2-weighted images [12**]:** which have a brighter appearance because CSF and fluid have greater signal intensities than tissue.T2 employed a long TE and TR for image production (traverse relaxation) (TR = 4000 msec, TE = 19 msec). T2 is appropriate for the oedema tissue because it is brighter for water and fluid.

T2-weighted imaging [12]: CSF and fluid have higher signal intensity than tissue, making them look brighter. In order to produce pictures (traverse relaxation), T2 required long times (TR = 4000 msec, TE = 19 msec). T2 is more visible to water and fluid, making it perfect for oedema tissues.

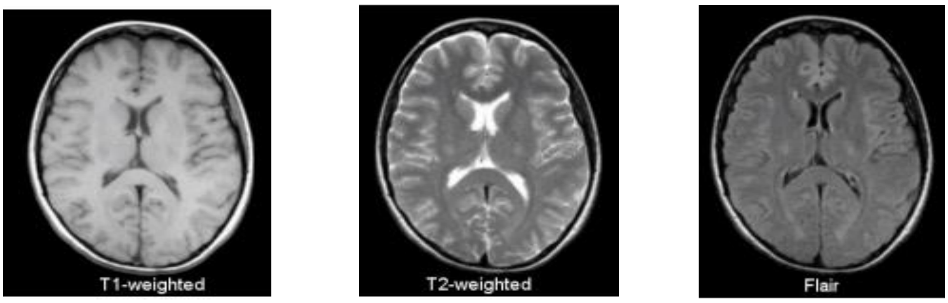

Figure 2 Type of MRI imaging technique

Table 1 below provides an illustration of the extra properties of T1, T2, and FLAIR**.**

TISSUES	T1--weighted	T2- weighted	FLAIR
CSF	Dark	Bright	Dark
White matter	Light	Dark grey	Dark grey
cortex	Grey	Light grey	Light grey
Fat(within bone marrow)	Bright	Light	Light
Inflammation (impurity)	Dark	Bright	Bright

Table 1 Describe the variations based on the many kinds of issues.

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Brain structure marks

On two-dimensional images, the brain is frequently visualized (slices). FIGURE Illustrates the coronal, horizontal (axial), and sagittal planes in which these slices are often made.

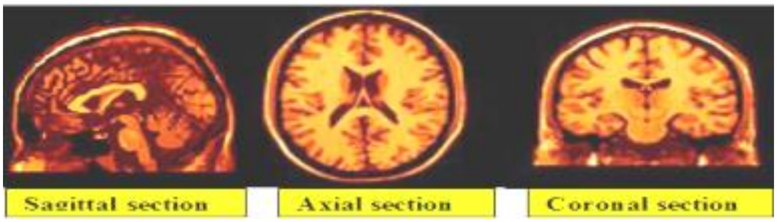

Figure 3 2D vision Brain

Need of the Study

The need for a Convolutional Neural Network (CNN) for the classification of brain tumors with deep learning capabilities is paramount in the field of medical diagnostics and healthcare. Brain tumors represent a critical health concern worldwide, with their early and accurate detection being essential for effective treatment and improved patient outcomes. Traditional methods of brain tumor classification often rely on manual interpretation of medical images such as MRI and CT scans. While these methods have proven valuable, they are time-consuming, subject to human error, and may not always provide the level of accuracy required for precise diagnosis. In contrast, a CNN with deep learning capabilities can revolutionize this process. By training on a vast dataset of brain images, the CNN can learn intricate patterns and features within the images that may be imperceptible to the human eye. This enables it to automatically classify brain tumors with a high degree of accuracy and speed, potentially saving valuable time in diagnosis. the use of CNNs in this context holds promise for early detection, which is critical for improving patient outcomes. Early diagnosis allows for timely intervention and treatment planning, potentially increasing survival rates and reducing the severity of neurological complications. the development of a CNN for brain tumor classification with deep learning capabilities is imperative to enhance the accuracy, efficiency, and speed of diagnosis, ultimately leading to improved patient care and outcomes in the field of neurology and oncology.

Literature Review

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Sakshi Ahuja et al. employed the brain segmentation method and the superpixel technique, respectively, to find brain cancers. The superpixel technique was used to partition the tumor between the LGG and HGG pictures.

Hajar Cherguif et al. used U-Net to segment medical image data into semantic categories. U-Net architecture was employed to create a successful convoluted 2D segmentation network. For testing and assessing the proposed model, the BRATS 2017 dataset was utilized. There were 4 deconvolutional layers, 27 convolutional layers, and a Dice coef of 0.81 in the proposed U-Net architecture.

Chirodip Lodh Choudhury et al., A Convolutional Neural Network model was utilised in conjunction using methods of deep learning that included deep neural networks to provide accurate results from MRI scans. It was feasible to attain a 96.05% accuracy rate and a 97.33 F-score.

Ahmad Habbie et al., An active contour model was used to analyze MRI T1-weighted images and determine whether a brain tumor might be present. Analysis was done on the effectiveness of morphological active contours with and without edges, snake active contours, and morphological geodesic active contours. According to the data, MGAC performed the best out of the three.

Neelum et al., used a concatenation approach in this paper's deep learning model and examined the likelihood of developing a brain tumor. Brain tumors were identified and classified using Inception-v3 and DenseNet201, two pre-trained deep learning models. For the purpose of classifying tumors, the Inception-v3 model was pre-trained to extract the features. A softmax classifier then completed the classification portion.

Ms. Swati Jayade et al., The use of hybrid classifiers was made. The feature collection for this investigation was produced using the Gray level Co occurrence Matrix (GLCM) feature extraction technique. To boost effectiveness, a hybrid approach to learners using KNN and SVM classifiers was suggested.

DR. Akey Sungheetha, DR. Rajesh Sharma R. et.al. used the Gabor transform along with the soft and hard clustering to identify edges in the CT and MRI images. We used 4500 MRI images, 3000 CT images, and a combined total of 2000 MRI images. To divide similar features into smaller groups, K-means clustering was employed. Author used fuzzy c means to represent the images as histogram properties**.**

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Parnian Afshar et al., categorized brain tumors using capsule networks using a bayesian approach. Capsule network was used in place of CNN to improve tumor detection results because CNN can lose crucial spatial information. BayesCap framework was suggested by the group.They utilised a reference brain tumour dataset to test the suggested model.

Brain Tumor Detection and Segmentation:

Jinyan Hu, Yuan Wange et. al. To conduct the pixel-by-pixel segmentation of the brain tumor, F2 FCN was used. In order to increase the rate at which valuable features are reused, a feature reuse model was developed.

Amjad Rehman, Muhmmad Attique Khan et.al. Using this architecture, the tumor was successfully detected in MRI scans with weak contrast. The classification accuracy of tumor types improved from before when a model that is built by employing the extraction of the tumor images was used.

Wu Deng, Qinke Shi et. al. For the segmentation, a deep learning method combining CFR and HCNN in a single system was suggested. According to the experimental findings, segmentation resilience can be increased by integrating CRF, RRNN, and HCNN.

Suhib Irsheidat, and Rehab Duwairi et. al. The dataset's size was increased by 14 times through augmentation. The classification of MRI images is the purpose of ACNN. Label 1 (indicating a tumour) and label 0 are used to label images (not having tumor).

Balakumaresan Ragupathy et.al. the performance of the suggested technique is assessed. The suggested method is contrasted with the current method in order to evaluate the model's performance.

Moumen T.Elmegy, and Khaled M.Abo-al Magad et.al., To determine whether a distinct class exists, and each classifier was trained using two classes. The segmentation of all three tumor sections improved significantly as a result of the experimental findings.

Bhagyashri H.Asodekar, Sonal A.Gore, and A.D Thakare et.al., Using methods for image processing Segmenting brain tumors is done, and feature extraction is done with shape-based features. To identify both malignant and benign brain tumors, extracted shape-based features are provided to ML, as well as VM and random forest algorithms.

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Bojaraj Leena, and Annamalai Jayanthi et.al. There were a total of five phases in the examination of the suggested model. The main objective of the paper was to pick the hidden neurons in the DBN first, followed by the bounding limits, using the new hybridization optimization approach.

Yakub Bhanothu, Anandhanarayanan Kamalakannan et.al., In the suggested systems, the fundamental layer (classifier network and region proposal network) was VGG-16, a CNN architecture. This research paper can be expanded upon to calculate the tumor's percentage area in relation to the human brain region.

Xiaoliang Lei, Xiaosheng Yu et.al., With the help of the method described in this paper, a sparse representation model of the shape of a brain tumor was created. It was created a method energy function based on a level set.

Masoumeh Siar, and Mohammad Teshnehlab et.al., The feature extraction algorithm and CNN were combined to perform the classification and segmentation. The accuracy of CNN was determined using the RBF classifier and the DT classifier.

Sharan Kumar et.al., A deep learning technique called Dolphin-SCA based depp CNN was proposed All of the following steps were completed: preparing, segmenting, extracting features, and classifying data.

P.G Rajan, and C. Sundar et.al., The KMFCM was employed because of its ability to handle a greater number of segmentation issues while requiring little processing time. In this process, the amount of white and black pixels, and the location where the tumor was found.

R. Pitchai, P. Supraja et.al., The segmentation of the brain tumor should be done using a model that An ANN and fuzzy K-means algorithm combination was used to introduced. The overall accuracy of the method was 8% higher than K-Nearest Neighbor methodology.

L. JanyShabu; C. Jayakumar et.al. Using SVM methodology, a report related to a systematic way of identifying brain tumor cells is produced. This article talks about how many people are diagnosed with gliomas each year. While separating, identifying, and extracting contaminated tumors areas from magnetic resonance imaging is important, it is challenging when researchers think about the assessment rating due to fatal error. To get around these limitations, classification and segmentation methods that are robotic and semi-automatic are currently being deployed. The proposed technique uses Otsu thresholding and fuzzy k means clustering logic to segment data. Additionally, brain images are recognized using SVM and intermediate

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outputs at the grey level with color and texture data taken from the photos. The input images are from the publicly available TCIA data archives dataset and a few other brain images from a nearby diagnostic facility that has treated 20 different patients. According to the simulation results , Support Vector Machine can classify normal and pathological cells with 98.51 percent accuracy.

RajatMehrotra; M.A. Ansari; Rajeev Agrawal et.al., This work deals with the detection and classification of LGG and HGG brain tumors using machine learning. Gliomas, benign brain tumors that develop from brain cells, are covered in this page. Low degree (slowly forming) or higher degree gliomas are two different types of gliomas (rapid developing). To choose the best course of treatment for a patient, doctors simply grade the patient's brain tumor based on the presence of gliomas. The tumor's condition is important for treatment. In order to further categories aberrant brain cancers into LGG or HGG brain tumors, this study will propose a computerized approach for separating functional brain from aberrant brain with tumor in MRI image data. The SVM logic, which diagnoses the abnormal brain tumors in the HGG and LGG, is a crucial component of the created framework once features are extracted and minimized.

Conclusion

The review of deep learning algorithms for brain tumor classification underscores their transformative potential in the field of medical imaging and healthcare. As we have seen, deep learning techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown remarkable promise in automating and improving the accuracy of brain tumor diagnosis. These algorithms have proven their ability to extract intricate patterns from complex medical images, leading to more precise and timely classifications of brain tumors. This not only reduces the burden on healthcare professionals but also offers the potential for earlier interventions and improved patient outcomes. However, it is essential to recognize the challenges that lie ahead, including the need for larger and more diverse datasets, model interpretability, and addressing issues of bias in AI systems. As deep learning continues to evolve, there is a clear path for enhancing its clinical adoption by integrating multi-modal data and incorporating explainable AI techniques. this overview highlights the pivotal role of deep learning in advancing brain tumor classification, offering a glimpse into the future of more efficient, reliable, and accessible healthcare solutions for patients facing this formidable medical challenge.

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