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Machine Learning Based Brain Tumor Detection and Classification: Review and Future Perceptions

Ankush[1], Meenakshi Arora[2], Rohini Sharma[3]

Student, Sat Kabir Institute of Technology and Management, Ladrawan, India[1]

Assistant Professor, Sat Kabir Institute of Technology and Management, Ladrawan, India[2]

Assistant Professor and Corresponding Author, GPGCW, Rohtak, Haryana, India[3]

ABSTRACT: Brain cancer is a destructive and life-threatening disease that imposes immense negative effects on patients' lives. Therefore, detection of brain tumors at an early stage improves the impact of treatments and increases patients' survival rate. However, detecting brain tumors in their initial stages is a demanding task and an unmet need. Management of brain tumors is based on clinical and radiological information with presumed grade dictating treatment. Hence, a non-invasive assessment of tumor grade is of paramount importance to choose the best treatment plan. Convolutional neural networks (CNNs) constitute a widely used deep learning approach that has frequently been applied to the problem of brain tumor diagnosis. Such techniques still face some critical challenges in moving towards clinic application. The main objective of this work is to present a comprehensive review of studies using CNN architectures to classify brain tumors using Magnetic Resonance Imaging (MRI) with the aim of identifying useful strategies for and possible impediments in the development of this technology. Diagnosing and segmenting brain tumors usually begin with Magnetic Resonance Imaging (MRI) on the brain since MRI is a noninvasive imaging technique. The current review provides an analysis of the performance of modern methods in this area. Moreover, various image segmentation methods in addition to the recent efforts of researchers are summarized.

KEYWORDS: Brain Tumor, Machine Learning based Classification, Magnetic Resonance Imaging

I. INTRODUCTION

Protractible lesions originating in the brain are known as brain tumors. Based on their impulsivity, they can be categorized as malignant (cancerous) or benign (non-cancerous) using the WHO rating system (1-4) for tumors, with 4 representing their malignancy [1]. Brain tumors that are malignant invade the connective tissue around them with varying degrees of aggression. The most prevalent and aggressive kind of malignant brain tumor is called glioblastoma (GBM), which is typically categorized as a grade 4 tumor with a poor prognosis. [2]. Additionally, brain tumors can be classified as primary or secondary brain tumors based on where they originate; the former normally start in the brain, while the latter generally start in an alternate region [3].
Figure 1 represents some advanced types of tumors. Each row depicts different type of brain tumor [4].

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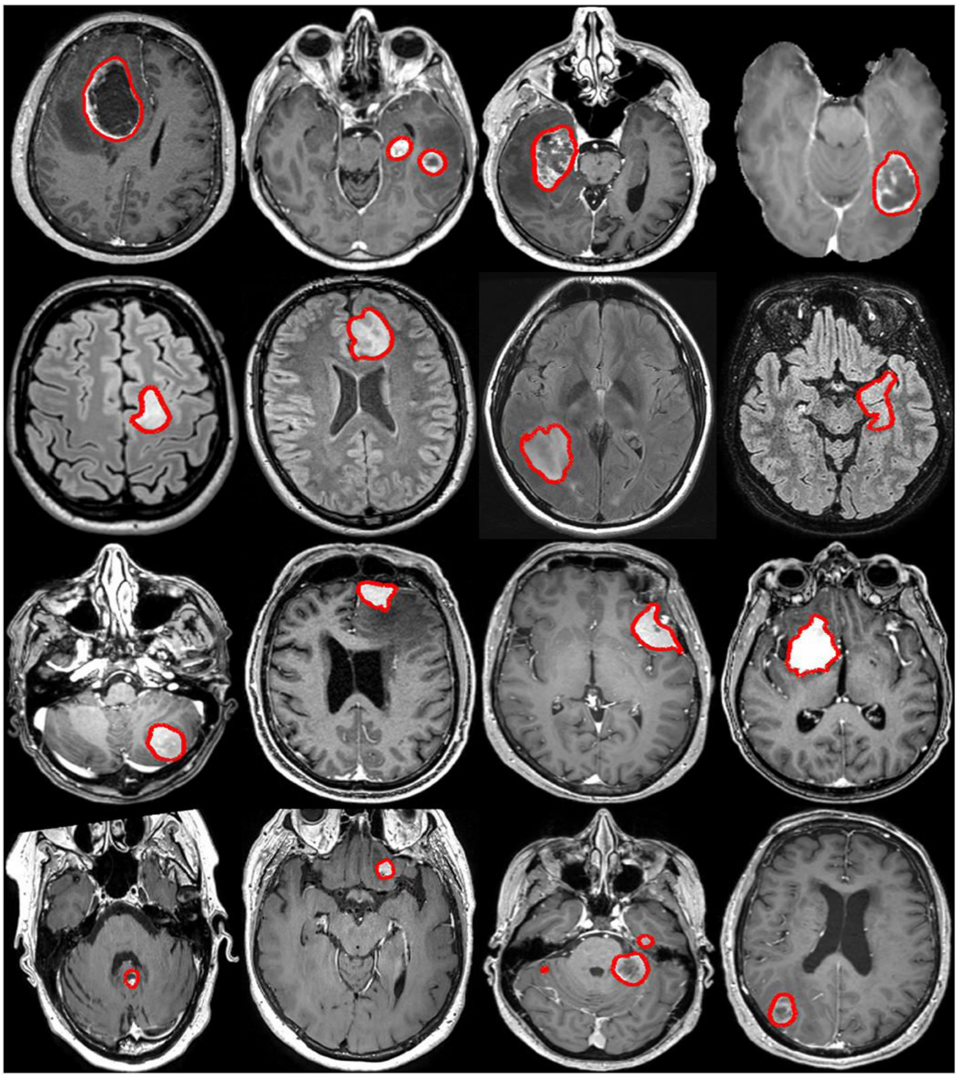

Figure 1: (row 1): Glioblastoma, (row 2): lower grade glioma, (row 3): meningioma, (row 4): metastasis

Radiological and clinical data currently constitute the basis for diagnosis and treatment. In order to evaluate the extent of the tumour, predict its grade, and measure its response to therapy, magnetic resonance imaging (MRI) is the premier method to diagnose patients with brain tumours [5]. However, standard imaging has severe drawbacks in these areas [6]. The implementation of innovative acquisition technologies aims to enhance lesion characterisation, therapy inspection, and handling [7]. On the other hand, fresh approaches to image processing have gained popularity due to the abundance of knowledge found in radiological pictures [8].

In this regard, segmenting and classifying brain tumours has become essential for image analysis. There are various techniques for classifying brain tumours, involving computer-aided and manual categorization. Brain tumour classification by hand takes a long time [9] and is prone to inaccuracy [10]. Yet it is impossible to overlook manual classification since it remains the pinnacle of accuracy for clinical care and serves as a benchmark for other methods. An overview of brain tumour segmentation and classification methods is presented in this paper, with a focus on CNN-based and machine learning-based methods. This study's major goal is to give a thorough analysis of research that employ machine learning techniques to categorise brain tumours using magnetic resonance imaging (MRI) in order to discover practical approaches and potential roadblocks in the advancement of this technology. With a focus on ML-based, CNN-based, and DL-based approaches, this study provides a survey on brain tumour segmentation and classification strategies. Along with recent successes, pertinent research difficulties, and future research prospects are highlighted in this paper.

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II. RELATED BACKGROUND

2.1 Types of Magnetic Resonance Imaging (MRI)

Standard MRI: The most crucial imaging test for astrocytomas is the MRI. Generally speaking, if the tumour gets bright on imaging or picks up contrast, it is likely a higher-grade astrocytoma. [11]. Figure represents standard MRI [13] and we observe that the hippocampal atrophy and signal anomalies are not visible on the standard MRI (A).

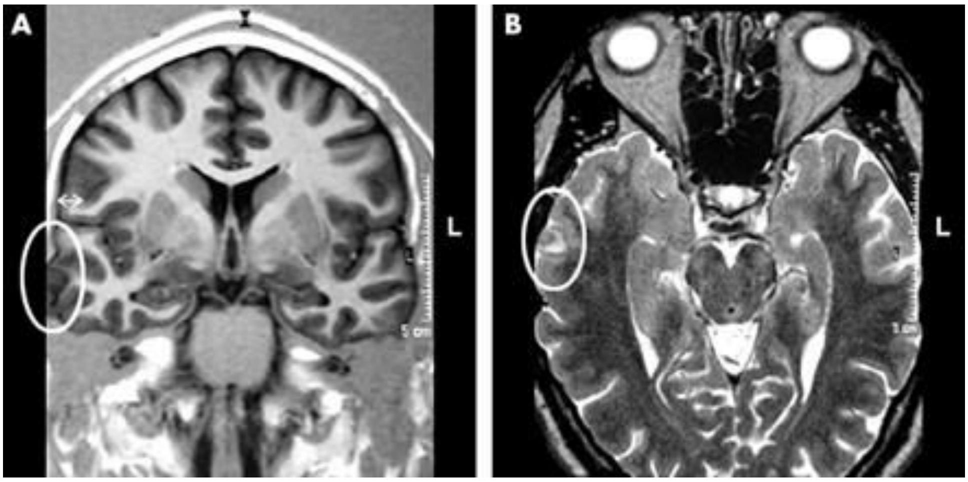

Figure 2: (A) T2 weighted standard MRI (B) epilepsy dedicated MRI angulated cardinally

MRI spectroscopy (MRS): This imaging technique, which is based on (MRI), uses the distinction between substances that are plentiful in tumours and normal brain tissue—such as choline—to offer details on the chemical structure of the tumour. This imaging modality is a graphic that shows the concentration of each molecule in a selected brain region: If NAA levels are higher than choline levels, this would point to a healthy brain. On the other hand, the reverse suggests a tumour. While less precise and conclusive than a normal biopsy, this method might be regarded as non-invasive tissue sampling [12]. In a healthy person, Figure shows an axial T2-weighted magnetic resonance image displays a single voxel of interest (white box) for MR spectroscopy inside the brain tissue [14].

FORMS OF BRAIN TUMOR

There are two types of brain tumors primary and secondary. In case of primary type of brain tumour, tumors instigate from the brain itself or its ancillary tissues however in case of secondary type of brain tumor the cancer cells have extended from tumors positioned elsewhere in the body to affect the brain (i.e., brain metastasis).

Gliomas are common subtype of brain tumours that originate from the glial cells, which is the supporting cell population of the brain. The less invasive structures are known as diffuse lower grade gliomas (LGGs), and they get a rating between 2 and 3. The more invasive structures are called high-grade gliomas (HGGs), and they are rated between 3 and 4. Meningiomas are tumours originating from the meninges, which constitute the exterior membrane covering of the brain. Other, less common tumour types exist in addition to the above broad groups (e.g., in the the hypothalamus, sellar, or brain areas). The biology, prognosis, and course of treatment vary depending on the type of tumour (3, 4). High-grade gliomas, which have a short overall 5-year survival rate and are among the most challenging diseases to treat, are the most prevalent basic malignant brain tumour type in people.

Glioblastoma Multiforme

Glioblastoma (GBM) is an invasive brain tumour that grows quickly. It is also known as a grade IV astrocytoma. It usually is not transmitted to other organs, but it does penetrate the neighbouring tissue of the brain.

GBMs can develop from lower-grade astrocytomas or occur in the brain from scratch. The cerebral hemispheres, particularly the frontal and temporal lobes, are where adult GBM most frequently develops. It is crucial to seek professional neuro-oncological and neurosurgical care as soon as possible since GBM is a deadly brain cancer that, if left untreated, can kill a person in six months or less. This can have an impact on the patient's chances of surviving. With 47.7% of all cases, glioblastoma is the most prevalent malignant brain and other CNS tumour. The incidence of glioblastoma is 3.21 per 100,000 people. The diagnosis is more common in men than in women, with a median age of 64. About 40% of patients survive in the first year following diagnosis and 17% in the second. Reduced allergy susceptibility, weakened immune system, and previous therapeutic radiation exposure are risk factors for glioblastoma.

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Glioblastoma risk is significantly increased by a number of genetic cancer syndromes, such as Lynch syndrome and Li-fraumeni syndromes.

Brain tumours can be precisely located using advanced imaging technologies. Magnetic resonance imaging (MRI) and computed tomography (CT or CAT scan) are examples of diagnostic tools. Moreover, tissue samples and tumour excision in surgery may benefit from intraoperative MRI guidance. Utilising magnetic resonance spectroscopy (MRS), the chemical profile of the tumour is investigated. There are hints regarding brain invasion, cerebral edoema, and tumour cellularity from other imaging patterns. While GBMs frequently exhibit core necrosis and significant contrast enhancement, low-grade tumours typically show little to no contrast enhancement.

Low-grade gliomas (LGGs)

In contrast to high-grade gliomas, low-grade gliomas (LGGs) are a varied class of primary brain tumours that often develop more slowly and have a longer prognosis. LGGs typically occur in young, relatively healthy individuals. The location, histology, molecular profile, and patient characteristics all play a role in the course of action, which vary and can involve radiation, surgery, chemotherapy, observation, or a combination of these. Furthermore, the possible advantages of treatment for this kind of brain tumour, which has a lengthy prognosis and survival time, need to be carefully balanced against any possible risks associated with it. A mix of imaging, histology, and molecular diagnostic techniques is used to make the diagnosis of LGGs. Low-grade gliomas show up on computed tomography scans as diffuse, low-attenuation regions. As the preferred imaging modality at the moment, conventional magnetic resonance imaging (MRI) frequently shows homogeneous LGGs with low intensity of signal on T1-weighted sequencing and hyperintensity on T2-weighted and Fluid-Attenuated Inversion Recovery (FLAIR) sequencing. Figure shows the MRI scan of a low grade Glioma [16].

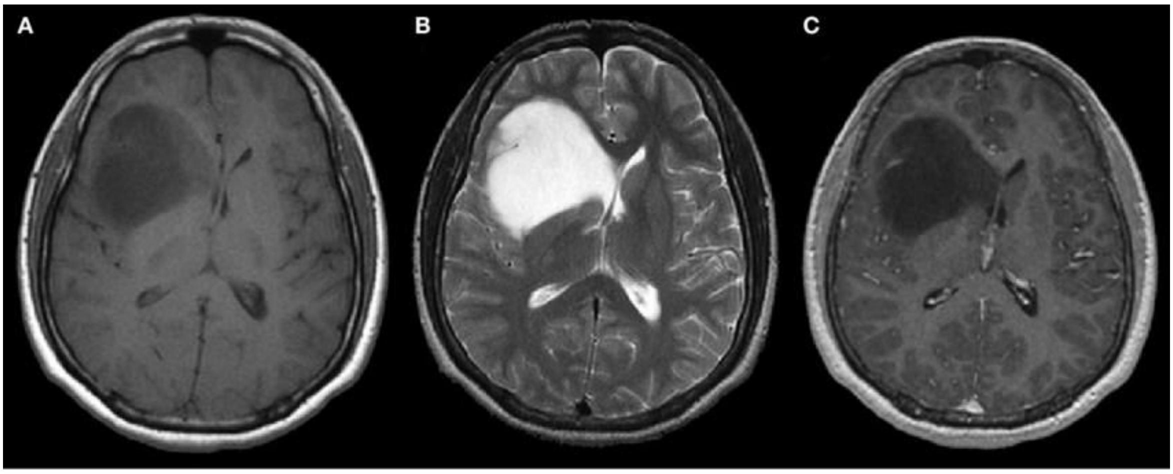

Figure 3: Low-grade glioma (A) T1 sequence showing the right frontal lobes T1 contraction (B) T2 sequence displaying hyperintensity (T2 prolongation) at the glioma location (C) Glioma contrast-enhanced scanning demonstrates no discernible contrast increase

Meningioma

A meningioma is a tumour that develops from the membranes that cover the brain and spinal cord, known as the meninges. It falls under this category even if it isn't strictly speaking a brain tumour since it has the potential to compress or squeeze nearby brain tissue, nerves, and blood vessels. The most frequent kind of tumour to develop in the head is meningioma. For many years, many meningiomas expand rather slowly and without presenting any symptoms. However, their impact on surrounding nerves, arteries, or brain tissue can occasionally result in severe impairment. Meningiomas can happen to anyone at any age, however they are more prevalent in women and are frequently found when they are aged. Meningiomas do not usually need to be treated right away and can be watched over time because they grow sluggish in most cases and frequently show no signs at all.

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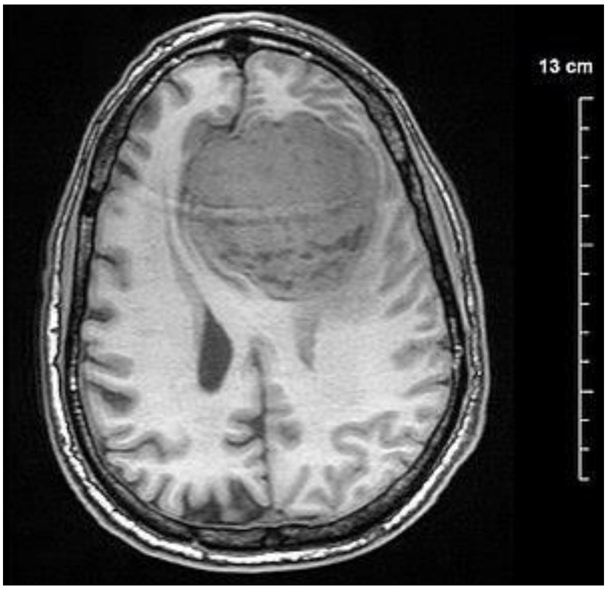

Figure 4: A brain CT scan that shows the emergence of a meningioma [17]

Metastasis

When cancer spreads to an area of your body other than its original site, it is said to have metastasized. Although they can have somewhat distinct meanings, the words "metastatic cancer," "advanced cancer," and "stage 4 cancer" can similarly be used to denote metastasis. Large malignancies that haven't migrated to other body parts might also be referred to as advanced cancer. Most frequently, metastases occur when cancer cells separate from the primary tumour and enter the lymphatic or circulatory systems of the body. The body uses these systems to transport fluids. This implies that when cancer cells stay and thrive in another region of the body, they have the ability to spread far from the initial tumour and generate new tumours. Additionally, cancer cells from the primary tumour may split off and spread to neighbouring organs like the liver, lungs, or bones.

Machine learning Based Brain Tumor Classification

The growth of CAD systems has been rapidly accelerated by machine learning [19]. categorising objects of concern, such as lesions, into different categories based on input attributes is one of the newest uses of machine learning in CAD [20]. Finding or learning useful aspects that effectively depict regularities or trends in data can be used in machine learning to accomplish a variety of image analysis tasks. But traditionally, relevant or task-relevant characteristics are primarily created by human specialists using their domain knowledge, which makes it difficult for non-experts to use methods of machine learning. Furthermore, traditional machine learning methods can only detect superficial linear relationships, while the biology underpinning living organisms is several orders of magnitude more complex [21].

Convolutional neural networks Based Brain Tumor Diagnosis

Convolutional neural networks (CNNs) constitute a widely used deep learning approach that has frequently been applied to the problem of brain tumor diagnosis. Its architecture enables it to instinctively acquire the features that are significant for a problem using a training corpus of adequate diversity and quality, which addresses the shortcomings of earlier deep learning systems [22]. Due to its exceptional performance with extremely high precision in a research environment, CNNs are now gaining support for the categorization of brain tumours [23].

Deep learning has demonstrated exceptional performance in medical image analysis these days, particularly in the categorization of brain tumours. Compared to traditional machine learning techniques, deep learning networks have demonstrated superior accuracy [24]. CNNs have gained a great deal of recognition in the field of deep learning for its ability to automatically identify deep features by adjusting to minute variations in the pictures [22]. Deep features are those that come from additional pertinent characteristics that are used to generate the final output of the neural network.

Brain Tumor Detection and Classification Using Deep Learning

In recent times, deep learning (DL) techniques have gained popularity in the development of computerized systems that can quickly and effectively diagnose or segment brain tumours. ZainEldin et al. [25] have optimized CNN hyperparameters using an adaptable dynamic sine-cosine fitness grey wolf optimizer (ADSCFGWO) process. It is composed of an Inception-ResnetV2 training model followed by a hyperparameters optimisation. The framework employs popular pre-trained models (Inception-ResnetV2) to improve the brain tumour diagnosis procedure. The result produced by the model is a binary 0 or 1 (0: Normal, 1: Tumour). In this study, new training data is digitally generated from the existing data using the data augmentation methodology. Picture augmentation is a type of data augmentation that generates modified depictions of the images in the training dataset. Numerous picture transformations, including random rotation, random zoom, horizontal and vertical shift, and horizontal and vertical flip, are applied to the input dataset. The accuracy of the proposed method is better than other classical machine learning methods (CNN, K-NN, SVM etc).

Saeedi et al. [26] used MRI brain images to detect brain tumor using a 2D CNN and an autoencoder with trained hyperparameters. Eight convolutional layers and four pooling layers constitute this network. Batch-normalization layers were added after all convolutional layers. A convolutional auto-encoder network and a convolutional network for classification that makes use of the final output encoder layer of the first half are both included in the updated auto-encoder network.

According to Alsubai et al. [27], owing to the peculiar distribution pattern of the lesions, there are still certain limits in the detection of brain tumours. It can be challenging to identify an area with few lesions since small areas typically appear healthy. It instantly decreases the precision of classification, therefore selecting and retrieving informative characteristics is difficult. The automatic classification of brain tumours in their early stages through the use of deep and machine learning techniques is important. In this study, a combination of deep learning models called CNN-LSTM (Convolutional Neural Network-Long Short Term Memory) was suggested for use in MRI brain tumour classification and prediction.

Medical machine learning programmes are unable to use medical data due to concerns about confidentiality. For instance, utilising image-based classification to diagnose brain tumours is challenging due to the absence of brain MRI scans. Deep Convolutional GAN (DCGAN) and Vanilla GAN are two instances of GAN designs used for image generation. The authors proposed [47] a BrainGAN model, for generating and classifying brain MRI images using GAN architectures and deep learning models. Three models are used: CNN, ResNet152V2, and MobileNetV2. The deep transfer models are trained using images produced by DCGAN and Vanilla GAN, and their efficacy is assessed using a test set of actual brain MRI scans. According to the experiment's results

Reference and Year	Tumor Type	Method	Model Used	Dataset	Performance
[25], 2022	Glioma	adaptive dynamic sine-cosine fitness grey wolf optimizer	CNN based Inception-ResnetV2	BRaTS 2021 Task 1 dataset.	Achieve an accuracy of 99.98% with Inception-ResnetV2 Model
[26], 2023	Glioma, Meningioma, and Pituitary gland tumors	auto-encoder neural network	CNN with 64 Filters and multiple layers	3264 T1-weighted Dataset [29]	training accuracy of auto-encoder network is 95.63% and of 2D CNN is 96.47%.
[27], 2022	All types of Tumors	Data Preprocessing+ thresholding+ extreme point computation+ Data Extraction	CNN-LSTM	MRI brain image dataset.	classification accuracy of 99.1%, a precision of 98.8%, recall of 98.9%, and F1-measure of 99.0%.
[28], 2023			CNN, MobileNetV2, ResNet152V2	Tumor and No-Tumor brain MRI images. (Total 1400 images)	ResNet152V2 obtained 99.09% accuracy, 99.12% precision, 99.08% recall

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