Advancements In Artificial Intelligence for Brain Tumor Detection: A Comprehensive Survey

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ABSTRACT

Brain tumors are a group of diseases characterized by abnormal growths of cells in the brain that can cause severe neurological symptoms. In recent years, the advent of artificial intelligence (AI) techniques has shown great promise in enhancing brain tumor detection. This survey research discusses methods and techniques used for AI-based brain tumor detection. Brain tumors pose significant health risks, necessitating accurate and timely detection for effective treatment. The study defines brain tumors and emphasizes the need for precise detection methods due to tumor variations. Biomarkers associated with brain tumors are investigated, highlighting their potential as diagnostic and prognostic indicators. The utilization of deep learning (DL) models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and 3D CNNs, is examined, providing a comparative analysis of their strengths and limitations. The importance of datasets, such as TCIA, BRATS, and ISLES, is discussed in training and evaluating AI models for brain tumor detection. This survey aims to contribute to the understanding and progress of AI-based brain tumor detection along with the comparison of some deep learning models, providing insights for researchers and healthcare professionals working towards improving patient outcomes.

Keywords: *Brain tumor; Artificial Intelligence; Tumor detection; Diagnosis; Image Preprocessing; Deep Learning; Neural Networks, Molecular biomarkers.*

1. INTRODUCTION

The brain serves as the main control center of the body and manages all of its activities, including movement, sensation, perception, and cognitive processes. The brain consists of three primary components: the cerebrum, and cerebellum brainstem. The largest par, and is the cerebrum which does many important things like controlling our senses and movements and more complex things like thinking, remembering, and making decisions. The cerebellum is at the back of the brain and helps us to move and stay balanced [1]. The brainstem is responsible for connecting the brain to the spinal cord and controlling essential functions like breathing, a heartbeat rate, and the level of blood pressure, making it a vital

component of the central nervous system (CNS). Brain tumor (BT) can impact any region of the brain, depending on its location and type. A study published in the Journal of Neuro-Oncology stated that the frontal lobe is the most common location for gliomas, with the temporal and parietal lobes following closely behind in terms of frequency [2]. Tumors located in the frontal lobe can affect personality, judgment, and decision-making, while tumors in the temporal lobe can affect memory and speech.

Tumors in the parietal lobe can affect sensation and perception, while tumors in the occipital lobe can affect vision [3]. Another study published in the Journal of Clinical Neuroscience in 2020 found that BT situated in the back part of the skull, known as the posterior fossa, involving the cerebellum and brainstem, carries a greater chance of neurological impairments and inferior results as compared to tumors located in other regions of the brain [4]. Brain tumors can have varying effects on the brain, which depend on their size and location. They can cause several symptoms including headaches, seizures, difficulty speaking, weakness or numbness in the limbs, and changes in personality or behavior [5]. Brain tumor diagnosis and treatment can be complicated because the symptoms depend on where and how big the tumor is. Brain tumors can cause headaches, seizures, personality changes, and even loss of motor function or speech impairment, depending on where the tumor is located. Brain tumors can also cause other complications, such as hydrocephalus, increased intracranial pressure, and cerebral edema [6]. BT treatment depends on many factors, including the kind of tumor that the patient has, its location, size, grade, and overall health status. These factors are critical in determining the most appropriate course of treatment. Surgery, radiation therapy, chemotherapy, and targeted therapy are the most widely used methods for the treatment of BT. Surgery is usually the primary option to remove as much of the tumor as possible, followed by radiation or chemotherapy to eliminate any remaining tumor cells [7]. Targeted therapy is a recent therapeutic approach that employs drugs to hinder particular molecular pathways involved in tumor growth and survival.

Despite the significant progress in the oncology of brain tumors, they continue to pose a substantial challenge for patients, caregivers, and healthcare providers. Multiple factors, including the tumor's grade and subtype, location, and the age of the patient, can impact the prognosis of individuals with brain tumors. High-grade tumors are known for their aggressive behavior and difficulty in treatment, while low-grade tumors generally have a more favorable prognosis. However, even low-grade tumors may require long-term monitoring and treatment. Moreover, the side effects of treatment can be significant, such as cognitive impairment, fatigue, and neuropathy, which can greatly affect the patient's health [8]. The integration of Artificial Intelligence (AI) and Machine learning (ML) in brain tumor research and clinical practice can revolutionize the field of neuro-oncology and improve patient outcomes [9]. AI can provide more accurate and efficient diagnosis and treatment planning, reduce the risk of human error and bias, and enable personalized medicine based on individual patient characteristics and tumor biology. However, several challenges and limitations also exist, such as the need for large and diverse datasets, the risk

of over-reliance on technology, and the ethical and legal implications of AI [10]. The process of BT detection is shown in Figure 1. The presented figure illustrates a systematic methodology involving lesion enhancement, segmentation, and subsequent classification [11]. Recent advancements in medical imaging, particularly in the domain of brain tumor detection, have undergone a revolutionary transformation with the infusion of machine learning (ML) techniques.

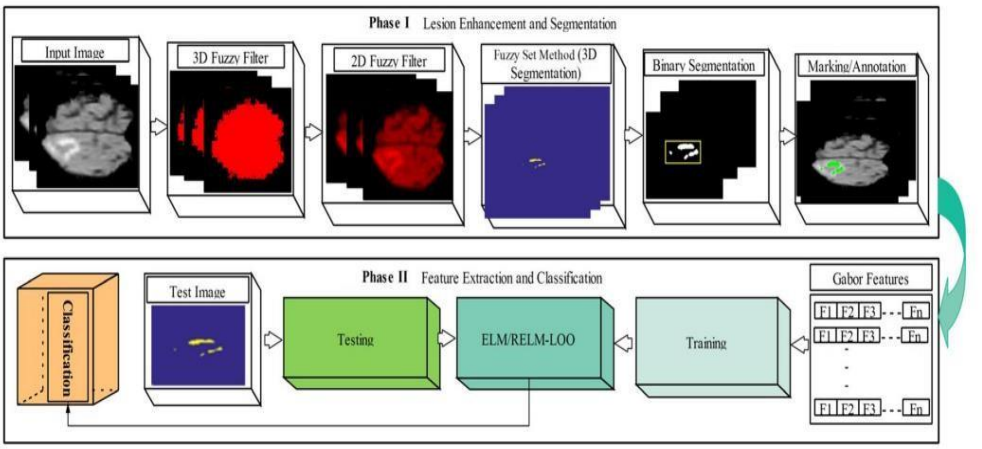

Figure 1. Process of Brain Tumor Detection [11]

2. BRAIN TUMOR

A medical condition that is marked by the abnormal growth of cells in the brain or surrounding areas. They can be categorized as primary tumors that originate in the brain or metastatic tumors that originate elsewhere in the body and spread to the brain.

2.1 PRIMARY BT

These are a type of tumors that originate within the brain and are classified into two main categories: gliomas and non-gliomas. Gliomas constitute the majority of the primary BT, accounting for roughly 80% of all cases. These tumors arise from glial cells, which are responsible for protecting and supporting neurons in the brain [5]. Various subtypes of gliomas exist, such as astrocytomas, oligodendrogliomas, and ependymomas, each possessing unique attributes and prognoses.

Non-gliomas refer to primary brain tumors that originate from different cell types within the brain, including meningiomas, pituitary adenomas, and schwannomas. Meningiomas are tumors that grow slowly and originate from the meninges, which are the protective membranes that cover the brain and the spinal cord. Pituitary adenomas develop from the pituitary gland located at the base of the brain and perform a vital function in regulating hormone levels in the body. Schwannomas are tumors that arise from Schwann cells, which

are *responsible* for insulating nerve fibers. *Primary BT* is classified according to their histological characteristics and graded on a scale of I to IV, based on the ability of their growth and potential to spread. The grades are [11]:

2.1.1 GRADE I TUMORS

They are the least aggressive and grow slowly. Typically, they are benign with well-defined borders, which makes them unlikely to metastasize to other regions of the brain or body. Examples include meningioma and pituitary adenomas.

2.1.2 GRADE II TUMORS

Although these tumors grow slowly, they have a higher chance of recurring after treatment. They are considered to be low-grade tumors and can be either benign or malignant. Examples include astrocytomas and oligodendrogliomas.

2.1.3 GRADE III TUMORS

These are considered to be malignant tumors, with cells that grow more rapidly and have more abnormal features than lower-grade tumors. They have the potential to spread to other parts of the brain or the spinal cord. Examples of grade III tumors are anaplastic astrocytomas and anaplastic oligodendrogliomas.

2.1.4 GRADE IV TUMORS

These are the most aggressive and fastest-growing tumors, with cells that are highly abnormal and tend to invade surrounding tissues. They are also known as glioblastomas and have a very poor prognosis.

2.2 METASTATIC BRAIN TUMOR

These tumors also referred to as secondary brain tumors, are a particular form of a BT that arises from other regions of the body and subsequently spreads (a process known as metastasis) to the brain. These tumors are more prevalent than primary BT and comprise roughly 10-30% of all BT diagnosed [12]. Notably, the most commonly observed types of cancer that can potentially metastasize to the brain encompass lung, breast, colon, kidney, and melanoma malignancies.

Compared to primary brain tumors, metastatic brain tumors are generally more aggressive, with the potential to grow and spread rapidly. Depending on their location and size, they can manifest a range of symptoms, such as headaches, seizures, limb weakness or numbness, changes in vision or speech, and cognitive dysfunction [13]. The methods used to treat metastatic BT may include surgery, radiation therapy, chemotherapy, targeted therapy, and immunotherapy. The prognosis for metastatic brain tumors can vary depending on factors such as the size and number of tumors, the type of cancer, and the patient's overall health. However, the overall survival rate for patients with metastatic BT is typically lower than for those with primary brain tumors.

3. BRAIN IMAGE MODALITIES

Brain imaging modalities are diagnostic techniques used to produce images of the brain and surrounding tissues. These images are used to diagnose and monitor brain diseases and conditions, such as BTs, stroke, and neurodegenerative diseases.

3.1 MAGNETIC RESONANCE IMAGING (MRI)

A strong magnetic field and radio waves are used to generate detailed images of the brain and other organs using a non-invasive imaging technique [14]. MRI is one of the most sensitive and specific imaging modalities for detecting brain tumors, and it is often used as the primary imaging modality for diagnosis, treatment planning, and follow-up information about the size, location, and characteristics of BT can be obtained through the use of MRI [15]. Tumor tissue typically appears as a region of abnormal signal intensity on MRI, which can be differentiated from normal brain tissue [16]. Additionally, MRI can be used to assess the extent of tumor infiltration into the surrounding brain tissue [17], as well as to detect the presence of edema (swelling) [18] and necrosis (dead tissue) [19] within the tumor. In addition to its diagnostic capabilities, MRI is also used to monitor the response of brain tumors to treatment, such as surgery, radiation therapy, and chemotherapy [20]. MRI can detect changes in tumor size [21], shape, and signal intensity over time [22], which can help clinicians assess the effectiveness of treatment and make adjustments as necessary [23]. Overall, MRI is an essential diagnostic tool in the clinical practice of BT, and its use is likely to continue to increase as technology and techniques continue to advance.

3.2 COMPUTED TOMOGRAPHY (CT)

It is another imaging modality commonly used for the detection of brain tumors. CT uses X-rays to produce detailed images of the brain and can be particularly useful in detecting bone abnormalities and small tumors that may be missed on MRI [24]. CT is often used as a first-line imaging tool for patients with suspected brain tumors, as it is faster and less expensive than MRI. CT scans can also be performed with contrast, which involves the injection of a contrast agent to highlight abnormal tissue in the brain [25]. Recent studies have shown that CT can be just as effective as MRI in detecting brain tumors, particularly for larger tumors or those located in the skull base or posterior fossa [26]. However, MRI is still considered the standard imaging modality for brain tumors due to its exceptional ability to provide soft tissue contrast and detect even small tumors [27].

3.3 POSITRON EMISSION TOMOGRAPHY (PET)

It is a medical imaging technique that uses a small quantity of radioactive material to generate three-dimensional images of the body [28]. In the context of BT, PET scans can be used to detect changes in glucose metabolism [29], which is an indicator of tumor growth and activity. In a PET scan, the medical professional injects a small amount of glucose that is radioactive in nature (or another tracer) into the patient's body, and cells in the brain subsequently absorb it. The radioactive material emits positrons, which collide with

electrons nearby, resulting in the production of gamma rays. A specialized ring of cameras surrounding the patient detects gamma rays, and a computer generates three dimensions of the brain based on the accumulated data [30]. The PET scan is particularly useful in detecting recurrent or residual brain tumors, as well as assessing the response of tumors to treatment [31]. It can also be used to mark a difference between benign and malignant tumors, as malignant tumors tend to have higher levels of glucose metabolism [32]. Recent studies have shown the potential of PET imaging with novel tracers in the detection and monitoring of BT. For example, a 2021 study published in the Journal of Nuclear Medicine found that a new PET tracer, FAMT, was able to accurately differentiate between glioma and non-glioma brain tumors with high sensitivity and specificity. Another study published in the same journal in 2020 showed that a PET tracer called FDG (Fluoro-D-glucose) can be used to assess the molecular characteristics of gliomas and predict their response to treatment [33].

3.4 SINGLE-PHOTON EMISSION COMPUTED TOMOGRAPHY (SPECT)

Another imaging modality is used for BT detection. SPECT uses a radioactive tracer that is injected into the bloodstream and travels to the brain [34]. The gamma camera detects the gamma rays emitted by the tracer to generate three-dimensional images of the brain. SPECT imaging can be used to differentiate between tumor tissue and healthy brain tissue, as tumor tissue tends to be more active and metabolically active than healthy brain tissue [35]. This technique can also be used to monitor the response of brain tumors to treatment, as changes in tumor activity can be detected through SPECT imaging [36].

A study published in the Journal of Nuclear Medicine Technology in 2020 evaluated the use of SPECT imaging in the diagnosis and management of brain tumors. The study found that SPECT imaging was useful in identifying the location and extent of brain tumors, as well as in monitoring the treatment response and detecting recurrent tumors [37]. A study published in the Journal of Neuro-Oncology in 2019 looked into the use of SPECT imaging to predict how fast a type of brain tumor called glioma might grow and how long patients with this tumor might survive. The study found that SPECT imaging helped make these predictions [38].

3.5 FUNCTIONAL MAGNETIC RESONANCE IMAGING (FMRI)

FMRI is a non-invasive imaging technique that utilizes magnetic fields and radio waves to visualize alterations in the blood flow within the brain. This technology has become an important tool in the detection of BT, as well as in the planning and monitoring of treatment [39]. FMRI is a technique that can help identify the brain regions affected by a tumor in BT detection [40]. This information can guide surgeons in planning the surgical approach for tumor removal and avoiding damage to critical areas of the brain that control vital functions such as movement, speech, and vision. Furthermore, fMRI can also be utilized to track the advancement of the tumor and assess the efficacy of the treatment [41].

4. MOLECULAR MARKERS FOR THE DETECTION OF BRAIN TUMORS

Molecular markers are specific molecules or genes that are expressed differently in normal cells versus tumor cells. They can be used as indicators of the presence of a tumor, as well as its subtype, aggressiveness, and response to treatment [42]. In brain tumor detection, molecular markers can be used to complement traditional imaging techniques like CT scans and MRIs. For example, a biopsy of a suspected brain tumor can be analyzed for the presence of specific molecular markers, which can help confirm the diagnosis and guide treatment decisions.

Several types of molecular markers have been identified for brain tumor detection, including [43]:

4.1 DNA MUTATIONS

These are changes in the DNA sequence that are associated with tumor development and progression. Examples include mutations in the IDH1 and IDH2 genes, which are found in a subtype of glioma [44].

4.2 GENE EXPRESSION PATTERNS

These are differences in the expression of certain genes between normal cells and tumor cells. Examples include the expression of the MGMT gene, which is associated with response to chemotherapy in glioblastoma [45].

4.3 PROTEIN MARKERS

These are proteins that are expressed differently in normal cells versus tumor cells [46]. Examples include the EGFR protein, which is overexpressed in a subtype of glioblastoma.

4.4 MICRORNA MARKERS

The small RNA molecules help in the regulation of gene expression and are differentially expressed in normal cells and tumor cells [47]. Examples include the miR-21 molecule, which is associated with glioma progression and poor patient prognosis.

Overall, the use of molecular markers in the detection of BT is a dynamic research field, which holds great potential in improving the diagnosis and treatment outcomes for patients with BT [42]. Although these markers have shown promise, their clinical utility needs to be validated through further studies, and their use in the clinic needs to be optimized. Table 1 shows the names of molecular markers along with the diseases associated with the respective mutations.

Table 1. Molecular Biomarkers for Brain Tumor

Biomarker and Associated mutation	Diseases	Prognostic	Diagnostic	Ref#
Mutations in the IDH1/2 gene	Oligodendrogliomas, astrocytoma, glioblastoma	✓	✓	[48]
Methylation of MGMT	Glioblastoma	✓	✗	[49]

promoter				
Amplification of EGFR gene	Glioblastoma	✓	✗	[49]
The Loss of PTEN gene	Glioblastoma	✓	✓	[50]
Mutations in TP53 gene	Glioblastoma	✓	✓	[49, 51]
Mutations in the ATRX gene	Glioma	✓	✓	[52]
Short arm deletion in chr no. 1 & long arm deletion in chr no. 19	Oligodendroglioma	✓	✓	[53]
Mutations in H3F3A or HIST1H3B gene	Diffuse midline glioma	✓	✗	[54]
Mutation in BRAF gene	Pilocytic astrocytoma	✓	✗	[55]

5. PREPROCESSING

Preprocessing is a crucial step in BT detection using MRI, as it aims to improve image quality [65] and reduce artifacts that can affect the accuracy of subsequent analysis [66]. Various preprocessing techniques [67] have been proposed in recent research, including bias, field correction [68], skull stripping [69], normalization [70], noise reduction [71], image enhancement [37], and feature extraction [39]. These techniques are used for intensity variations, removing non-brain tissue, aligning images from different modalities or time points, normalizing images to standard space, reducing noise, enhancing image contrast, and extracting relevant features for machine learning or other analysis [72]. A brief summary of publicly available Brain tumor datasets is given in Table 2.

Table 2. Summary of Datasets for BT Detection

Ref#	Dataset Name	Description	Modality	Year
[1]	BT- Figshare	Imbalanced MRI dataset for brain tumor categorization with weighted loss and deep feature fusion	MRI	2023
[2]	Local dataset	Extensive Brain metastatic(BM) legions	Automatic BM detection, lesion segmentation	2023
[58, 59]	The Cancer Imaging Archive (TCIA)	Large collection of publicly available cancer imaging data	MRI, CT, PET	2019
[60]	BRATS	Multimodal brain tumor dataset for segmentation tasks	MRI	2022
[61]	ISLES	Dataset for ischemic stroke lesion Segmentation (ISLES)	MRI	2022
[62]	LGG	Dataset containing lower grade glioma (LGG) brain tumor images	MRI	2020
[63]	ADNI	Neuroimaging data from subjects with brain tumors	MRI	2021
[64]	CPTACGBM	Proteomic and genomic data for glioblastoma	Proteomics, genomics	2016

5.1 IMAGE SEGMENTATION

It is an important and critical task in brain tumor detection, and diagnosis [73], as it involves separating different tissues in the brain and isolating the tumor region for further analysis. Various techniques of segmentation have been proposed in recent research, including thresholding, region growing, clustering, active contours, level sets, graph-based methods, and DL-based methods [74]. These techniques aim to accurately segment the tumor region while minimizing false positives and false negatives, which can affect diagnosis and the ways of treatment of brain tumors.

Recent research has shown that DL-based methods can achieve state-of-the-art performance in BT segmentation, with CNNs being the most commonly used architecture [75], [76]. Usually, these techniques involve training a CNN on an extensive dataset of annotated images [77] to acquire the features that differentiate tumors from non-tumor regions. Some data augmentation techniques [78], like rotation, scaling, translation, and flipping, can be used to increase the size of the training set and improve generalization [79]. Several studies have also proposed novel models or modifications to existing models to improve segmentation performance [80]. Along with the DL-based methods, other segmentation techniques have also been proposed in recent research. For example, graph-based methods have been used to model the relationships between different regions in the brain and improve segmentation accuracy [81]. Active contours and level sets have been used to incorporate prior knowledge about the shape and location of tumors to improve segmentation performance [82]. Hybrid approaches that combine multiple segmentation techniques have also been proposed [83]. A summary of image Segmentation Techniques for BT is given in Table 3.

Table 3: Summary of Image Segmentation Techniques

Ref#	Year	Segmentation methods	Datasets	Accuracy
[84]	2019	U-Net 2D structure	BRATS 2015 BRATS 2017	0.876%
[71]	2022	U-Net, DeeplabV3+	BRATS 2015/2018	0.23%
[85]	2020	3D U-Net architecture	BRATS 2018 Local hospital dataset	0.67%
[73]	2017	DeepLab, semantic image segmentation	BRATS 2015	0.78%
[79]	2020	3D fully CNN based on U-net CRF	BRATS 2017 MNI-HISUB25	95.88% whole MNI-HISUB25

5.2 NORMALIZATION

Normalization is an essential preprocessing step in BT detection and diagnosis. It is used to standardize the intensity values of the magnetic resonance images (MRI) across different patients and scanners, reducing inter-subject variability and improving the performance of subsequent processing steps [86]. There are various normalization techniques proposed in

recent research, including Z-score normalization, histogram normalization, quantile normalization, and scale-invariant feature transform (SIFT) normalization [79].
One commonly used normalization method is Z-score normalization, which transforms the intensity values of each voxel in the image to a standardized Z-score based on the mean and standard deviation of the intensities in the whole brain [87]. Histogram normalization is an alternative technique that adjusts the intensity distribution of an image to correspond to a given reference histogram, such as a healthy brain image or a population-based histogram [86]. Quantile normalization, on the other hand, matches the quantiles of the intensity distributions between the images, ensuring that the same percentage of voxels in each image has the same intensity value [88]. SIFT normalization is a more recent technique that uses local feature descriptors to normalize the images based on their scale and orientation, enhancing the contrast between the tumor and surrounding tissues [53, 55]. The choice of a normalization method depends on the characteristics of the data and the specific research question. Recent studies have shown that using a combination of different normalization methods can result in better performance of BT detection, and segmentation [89].

5.3 FEATURE EXTRACTION

Feature extraction is a crucial step in the detection of BT using artificial intelligence models. Researchers have utilized various techniques for feature extraction, such as wavelet transform [91], gray-level co-occurrence matrix [92], histogram of oriented gradients (HOG) [93], auto-encoder [94], discrete wavelet transform (DWT) [95], curve let transform [95], and texture feature extraction [96]. Deep CNNs have been employed for BT detection with feature extraction as a primary step [95, 97, 98]. Researchers have used a combination of CNNs and other machine learning models such as support vector machine (SVM)[99],[92], random forest [97], and k-nearest neighbors (KNN) [100]. The datasets used by researchers for brain tumor detection and classification vary widely. Some studies have used publicly available datasets such as the BraTS dataset [95, 97, 101], while others have used their customized datasets [93].

6. DL MODELS FOR THE DETECTION OF BT

DL models are a type of artificial intelligence that can automatically learn to identify patterns and features in complex datasets. They consist of multiple layers of interconnected artificial neurons that can process and analyze large amounts of data. Training DL models on vast datasets enables those to perform a variety of tasks, including image classification, object detection, and natural language processing [102]. In the context of BT detection, DL models can analyze medical images such as MRI scans and identify regions that are indicative of tumors [103]. They can learn to differentiate between healthy brain tissue and tumor tissue and can provide accurate and consistent results [104]. Recent studies have shown promising results for the use of DL models in BT detection. For example, a study published in 2019 used a DL model to detect BT in MRI scans with a high level of accuracy [90]. Another study of BT tumors is based on their histology [105].

a. ***Convolutional Neural Networks (CNNs)*** belong to the category of DL models, which are capable of learning and recognizing patterns and features in images**.** CNNs consist of numerous convolutional and pooling layers, followed by fully connected layers, primarily used for classification purposes. Analyzing medical images, such as Magnetic Resonance Imaging (MRI) scans, using CNNs can aid in the detection of brain tumors. A study published in 2018 used a CNN to detect brain tumors in MRI scans with a high level of accuracy [106]. Another study published in 2018 showed that a CNN could be used to differentiate between different types of brain tumors based on their appearance on MRI scans [75]. A 2019 study used a CNN to detect BT in pediatric patients with high accuracy and sensitivity [107]. A 2017 study demonstrated that a CNN could accurately classify brain tumors based on their genetic profile [108].In 2022, a study showed that a CNN could be used to detect BT in MRI scans with higher accuracy than human experts [109]. Another 2021 study demonstrated that a CNN could accurately differentiate between benign and malignant BT based on MRI scans [110].

b. ***Recurrent neural networks (RNNs)*** are a type of DL model that is designed to process sequential data, where the output from the previous step is fed back as an input to the current step. In the context of BT detection, RNNs have been used to analyze time-series data from electroencephalogram (EEG) recordings to predict tumor progression and recurrence [111]. For example, one study used a combination of RNNs and CNNs to predict the survival time of patients with glioblastoma multiform based on MRI images [112]. Another study used a DL model based on RNNs to analyze EEG recordings and predict the progression of glioblastoma [113]. Overall, RNNs are a powerful tool for analyzing sequential Data in the context of BT detection could potentially improve patient outcomes by enabling earlier detection and more accurate prognostication [114].

c. ***Three-dimensional convolutional neural networks (3D CNNs)*** are DL models that can extract spatial features from volumetric data. In the context of BT detection, 3D CNNs have shown great promise due to their ability to capture complex patterns and relationships in three-dimensional medical imaging data [115]. Researchers have explored the use of 3D CNNs for brain BT detection by analyzing MRI images. One study used 3D CNNs to segment BT from MRI scans and compared their results to manual segmentation by radiologists [115]. Another study developed a 3D CNN model to classify BT based on MRI images and achieved high accuracy in tumor classification [116]. In addition, researchers have also used 3D CNNs to assist in tumor grading and distinguishing between different types of brain tumors. For example, a study proposed a 3D CNN model to predict the molecular subtypes of gliomas based on MRI scans [117]. Overall, 3D CNNs have shown great potential in improving the accuracy and efficiency of BT detection and classification [118]. Table 4 shows the comparison of DL models.

Table 4. Comparison of Existing Deep Learning Models

DL Model	Description	Architecture	Feature Extraction	Temporal or Spatial Information	Training Process	Performance Measures
CNN	Effective for image classification and segmentation tasks in brain tumor detection.	Convolutional layers with pooling and fully connected layers	Automatically learns relevant features from medical images	N/A	Backpropagation with gradient-based optimization	Accuracy, precision, recall, F1 score
RNN	Suitable for processing sequential and time-Series data in brain tumor analysis.	Recurrent layers (e.g., LSTM, GRU)	Captures temporal dependencies in data	Models temporal information across sequences	Backpropagation through time	Accuracy, precision, recall, F1 score
3D CNN	Extends CNN to Work directly with 3D volumes, capturing spatial information in brain images.	3D convolutional layers with pooling and fully connected layers	Learns spatial features in 3D space	Captures spatial relationships in volumetric data	Backpropagation with gradient-based optimization	Accuracy, precision, recall, F1 score

7. EXISTING CHALLENGES AND LIMITATIONS IN BT DETECTION

Detecting BT is a challenging task as they can be small in size, have irregular shapes, and be located in critical brain regions, making it difficult to differentiate between healthy and cancerous tissues [119]. Despite the promising results of DL models for BT detection, some challenges and limitations still need to be addressed [120]. One of the main challenges is the lack of large annotated datasets, which can affect the generalization of the models and lead to overfitting [121]. In addition, there is a lack of standardization in the preprocessing of medical images, which can lead to inconsistencies in the data and affect the accuracy of the models [122]. Furthermore, some studies have shown that DL models can be sensitive to variations in image quality, such as noise and artifacts, which can affect the performance of the models [123].

Another limitation is the interpretability of the models, which can be a concern for clinical applications. DL models are often seen as black boxes, making it difficult to understand how they arrive at their predictions. This can be a significant barrier to the adoption of these models in clinical practice, as clinicians need to be able to interpret the results and make informed decisions based on them. There is a need for more research on how to make deep learning models more transparent and interpretable [124].

Moreover, DL models can be computationally expensive and require significant computing resources [125]. This can make it difficult to deploy these models in resource-limited settings hospitals or clinics. There is a need for more research on how to optimize the performance of deep learning models while minimizing their computational requirements [126]. Finally, there are ethical and legal challenges associated with the use of DL models for medical diagnosis. For example, there are concerns about privacy and data security when using medical images for training deep learning models. Additionally, there are questions about liability and accountability when using these models to make medical decisions. More research is needed to address these issues and ensure that the use of deep learning models for medical diagnosis is ethical, legal, and responsible.

In a study conducted in 2020, the authors investigated the use of DL algorithms for the automatic detection of BT in MRI images. The study reported that the major challenge in detecting BT using DL algorithms is the lack of annotated data, which limits the training and validation of the algorithms [127]. Another challenge highlighted in 2018 is the high variability in BT appearance and location, making it difficult to develop a single algorithm that can accurately detect all types of BT [128]. The high false-positive rate of AI and ML algorithms for BT detection is another limitation. As reported in one article, false-positive results can lead to unnecessary invasive procedures, which can be harmful to patients [129]. Data and model limitations along with the clinical challenges in the detection of BT are discussed in Table 5.

Table 5. Limitations and challenges of Deep Learning Models

Ref#	Data Limitations	Model Limitations	Clinical Challenges
[86]	Limited availability of annotated data for training deep learning models, variability in data quality, bias, and interpretability	High computational cost and storage requirements	Complex and variable nature of brain tumors, the need for accurate diagnosis and treatment planning
[87]	Limited sample sizes, imbalanced datasets, variability in imaging modalities and parameters	Overfitting and selection bias in model development	Limited generalizability across different patient populations and clinical settings, difficulty in distinguishing between tumor and normal tissue
[88]	Limited availability of large-scale, annotated datasets for detecting brain tumors	Limited performance of current image many population detection models	To detect manipulated medical images that can lead to incorrect diagnoses and treatments.
[89]	Lack of standardized protocols for data acquisition, preprocessing, feature extraction, and model training and validation	Limited generalizability of models to different datasets	reduce the variability of medical images caused by different imaging modalities, image resolutions, and image quality
[90]	Limited access to high-quality healthcare data for training and validation	Lack of standardization in AI development and evaluation	Ethical Considerations and potential biases in AI Applications
[91]	Limited availability of annotated data, variability in imaging protocols, and quality	Difficulty in interpretability and explainability of models	Integration of AI into clinical workflow, validation, and generalizability of models

[92]	Limited computational resources for developing and training deep learning models	Lack of optimization techniques	To develop deep learning models that can perform accurate diagnoses with a limited amount of computational resources, such as time and hardware.
[93]	Limited interpretability of deep learning models, overfitting, and selection bias	Hyperparameters	To develop deep learning models that can perform accurate diagnoses with a limited amount of computational resources, such as time and hardware.
[94]	Limited availability of annotated data for training deep learning models, limited sample sizes	Difficulty in identifying tumor boundaries and heterogeneity of tumors	Validation and generalizability of models to different populations
[95]	Difficulty in distinguishing between tumor and normal tissue	Difficulty in identifying tumor boundaries and heterogeneity of tumors	Need for interpretability and transparency in clinical decision-making
[96]	Limited availability of high-quality, annotated data for training and validation	Difficulty in interpretability and explainability of models	Limited generalizability across different patient populations and clinical settings needs for accurate diagnosis and treatment planning

8. CONCLUSION

Detecting BT using AI is a promising field with significant potential for improving the accuracy and efficiency of diagnosis. In this survey, we have explored the different types and subtypes of brain tumors, the various brain image modalities used in diagnosis, and the molecular markers that can aid in detecting brain tumors. Additionally, we have discussed several preprocessing techniques that can help enhance the quality of medical images and improve the performance of AI algorithms. Finally, we have reviewed some of the most promising deep-learning models that have been developed for the detection of brain tumors. The results of our survey show that the use of AI in the detection of brain tumors has several advantages over traditional methods, including increased accuracy, speed, and the ability to detect tumors in their early stages. However, there are still several challenges that need to be addressed, such as the limited availability of large-scale annotated datasets, the need for more robust and interpretable AI models, and the need to integrate AI with clinical workflows to ensure that patients receive timely and effective treatment. Overall, we believe that the continued development and refinement of AI-based methods for the detection of brain tumors will lead to significant improvements in patient outcomes and contribute to the advancement of our understanding of this complex disease.

9. REFERENCES

[1] A. Gajjar, G. H. Reaman, J. M. Racadio, and F. O. Smith, Brain Tumors in Children. Springer, 2018.

[2] A. Van Westrhenen, J. Senders, E. Martin, A. DiRisio, and M. Broekman, "Clinical challenges of glioma and pregnancy: a systematic review," Journal of Neuro-Oncology, vol. 139, pp. 1-11, 2018.

[3] L. M. DeAngelis, "Brain tumors," New England Journal of Medicine, vol. 344, no. 2, pp. 114-123, 2001.

[4] K. E. Robinson, C. E. Fraley, M. M. Pearson, J. F. Kuttesch, and B. E. Compas, "Neurocognitive late effects of pediatric brain tumors of the posterior fossa: a quantitative review," Journal of the International Neuropsychological Society, vol. 19, no. 1, pp. 44-53, 2013.

[5] S. Lapointe, A. Perry, and N. A. Butowski, "Primary brain tumors in adults," The Lancet, vol. 392, no. 10145, pp. 432-446, 2018.

[6] Y. Mizobuchi et al., "The risk of hemorrhage in stereotactic biopsy for brain tumors," The Journal of Medical Investigation, vol. 66, no. 3.4, pp. 314-318, 2019.

[7] C. N. de Leeuw and M. A. Vogelbaum, "Supratotal resection in glioma: a systematic review," Neuro-oncology, vol. 21, no. 2, pp. 179-188, 2019.

[8] I. Ahmad and F. A. Rathore, "Neurological manifestations and complications of COVID-19: A literature review," Journal of Clinical Neuroscience. 77, pp. 8-12, 2020.

[9] A. A. K. Abdel Razek et al., "Clinical applications of artificial intelligence and radiomics in neuro-oncology imaging," Insights into Imaging, vol. 12, pp. 1-17, 2021.

[10] S. A. Sheth, L. Giancardo, M. Colasurdo, V. M. Srinivasan, A. Niktabe, and P. Kan, "Machine learning and acute stroke imaging," Journal of neurointerventional surgery, vol. 15, no. 2, pp. 195-199, 2023.

[11] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, "Brain tumor detection and classification using machine learning: a comprehensive survey," Complex & Intelligent Systems, pp. 1-23, 2021.

[12] H. Zhang, L. Xu, Z. Zhong, Y. Liu, Y. Long, and S. Zhou, "Lower-grade gliomas: predicting DNA methylation subtyping and its consequences on survival with MR features," Academic Radiology, vol. 28, no. 7, pp. e199e208, 2021.

[13] A. A. Aizer et al., "Brain metastases: A Society for Neuro-Oncology (SNO) consensus review on current management and future directions," Neurooncology, vol. 24, no. 10, pp. 1613-1646, 2022.

[14] N. Weiskopf, L. J. Edwards, G. Helms, S. Mohammadi, and E. Kirilina, "Quantitative magnetic resonance imaging of brain anatomy and in vivo histology," Nature Reviews Physics, vol. 3, no. 8, pp. 570-588, 2021.

[15] G. Katti, S. A. Ara, and A. Shireen, "Magnetic resonance imaging (MRI)–A review," International Journal of Dental Clinics Clinics, pp. 5-70, 2011.

[16] N. J. Shafana and A. SenthilSelvi, "Analysis of AI-based Brain Tumor Detection and Diagnosis," in 2021 4th International Conference on Computing and Communications Technologies (ICT), 2021: IEEE, pp. 627-633.

[17] S. Sajid, S. Hussain, and A. Sarwar, "Brain tumor detection and segmentation in MR images using deep learning," Arabian Journal for Science and Engineering, vol. 44, pp. 9249-9261, 2019.

[18] T. J. Kaufmann et al., "Consensus recommendations for a standardized brain tumor imaging protocol for clinical trials in brain metastases," Neuro-oncology, vol. 22, no. 6, pp. 757-772, 2020.

[19] X. Jiang et al., "MRI of tumor T cell infiltration in response to checkpoint inhibitor therapy," Journal for Immunotherapy of Cancer, vol. 8, no. 1, pp. 1-12, 2020.

[20] M. Papadopoulos, S. Saadoun, D. Binder, G. Manley, S. Krishna, and A. Verkman, "Molecular mechanisms of brain tumor edema," Neuroscience, vol. 129, no. 4, pp. 1009-1018, 2004.

[21] R. Hustinx, M. Pourdehnad, B. Kaschten, and A. Alavi, "PET imaging for differentiating recurrent brain tumor from radiation necrosis," Radiologic Clinics, vol. 43, no. 1, pp. 35-47, 2005.

[22] A. Horská and P. B. Barker, "Imaging of brain tumors: MR spectroscopy and metabolic imaging," Neuroimaging Clinics, vol. 20, no. 3, pp. 293310-293321, 2010.

[23] C. S. Rao and K. Karunakara, "A comprehensive review on brain tumor segmentation and classification of MRI images," Multimedia Tools and Applications, vol. 80, no. 12, pp. 17611-17643, 2021.

[24] A. A. K. A. Razek, N. A. Elsebaie, O. A. Gamaleldin, A. AbdelKhalek, and S. K. Mukherji, "Role of MR imaging in head and neck squamous cell carcinoma," Magnetic Resonance Imaging Clinics, vol. 30, no. 1, pp. 1-18, 2022.

[25] F. S. D. Karomy, "Diagnostic Accuracy of MRI Compared to CCT in Patients with Brain Metastases," Medico-Legal Update, vol. 21, no. 4, pp. 275-281, 2021.

[26] L. d. O. P. Dias, "A new approach for pediatric posterior fossa semantic segmentation in magnetic resonance images," Universidade de São Paulo, 2022.

[27] A. Meola, J. Rao, N. Chaudhary, M. Sharma, and S. D. Chang, "Gold Nanoparticles for Brain Tumor Imaging: A Systematic Review," (in eng), Front Neurol, vol. 9, pp. 328- 335, 2018.

[28] T. R. DeGrado, T. G. Turkington, J. J. Williams, C. W. Stearns, J. M. Hoffman, and R. E. Coleman, "Performance characteristics of a wholebowhole-bodyanner," Journal of Nuclear Medicine, vol. 35, no. 8, pp. 13981406-13981415, 1994.

[29] A. Holzgreve, N. L. Albert, N. Galldiks, and B. Suchorska, "Use of PET imaging in neuro-oncological surgery," Cancers, vol. 13, no. 9, pp. 2093-2104, 2021.

[30] S. Quader, K. Kataoka, and H. Cabral, "Nanomedicine for brain cancer," Advanced Drug Delivery Reviews, pp. 114115-114124, 2022.

[31] N. Galldiks, P. Lohmann, N. L. Albert, J. C. Tonn, and K.-J. Langen, "Current status of PET imaging in neuro-oncology," Neuro-Oncology Advances, vol. 1, no. 1, pp. 1-11, 2019.

[32] T. Z. Wong, G. J. van der Westhuizen, and R. E. Coleman, "Positron emission tomography imaging of brain tumors," Neuroimaging Clinics, vol. 12, no. 4, pp. 615-626, 2002.

[33] M. Bordonne et al., "Brain 18 F-FDG PET for the diagnosis of autoimmune encephalitis: a systematic review and a meta-analysis," European journaJournalclear Medicine and Molecular Imaging, vol. 48, pp. 3847-3858, 2021.

[34] S. J. Lee and H. J. Park, "Single photon emission computed tomography (SPECT) or positron emission tomography (PET) imaging for radiotherapy planning in patients with lung cancer: a meta-analysis," Scientific RepoRtReports 10, no. 1, pp. 14864-14874, 2020.

[35] S. Yandrapalli and Y. Puckett, "SPECT Imaging," in StatPearls. Treasure Island (FL): StatPearls Publishing Copyright © 2023, StatPearls Publishing LLC., 2023.

[36] K. M. Davis, J. L. Ryan, V. D. Aaron, and J. B. Sims, "PET and SPECT imaging of the brain: History, technical considerations, applications, and radiotracers," in Seminars in Ultrasound, CT and MRI, 2020, vol. 41, no. 6: Elsevier, pp. 521-529, 2020.

[37] J. Zhang, K. S. Traylor, and J. M. Mountz, "PET and SPECT imaging of brain tumors," in Seminars in Ultrasound, CT and MRI, 2020, vol. 41, no. 6: Elsevier, pp. 530-540, 2020.

[38] K. Holcman et al., "99mTc-HMPAO-labeled leukocyte SPECT/CT and transthoracic echocardiography diagnostic value in infective endocaEndocarditis International Journal of cardiovascular imaging, vol. 35, pp. 749-758, 2019.

[39] V. Scarapicchia, C. Brown, C. Mayo, and J. R. Gawryluk, "Functional Magnetic Resonance Imaging and Functional Near-Infrared Spectroscopy: Insights from Combined Recording Studies," (in eng), Front Hum Neurosci, vol. 11, p. 419-423, 2017.

[40] J. W. Scott et al., "Contextual Challenges to Safe Surgery in a Resourcelimited Setting: A Multicenter, Multiprofessional Qualitative Study," (in eng), Ann Surg, vol. 267, no. 3, pp. 461-467, Mar 2018.

[41] Y. Guan et al., "A framework for efficient brain tumor classification using MRI images," (in eng), Math Biosci Eng, vol. 18, no. 5, pp. 5790-5815, Jun 25, 2021.

[42] W. Jelski and B. Mroczko, "Molecular and Circulating Biomarkers of Brain Tumors," (in eng), Int J Mol Sci, vol. 22, no. 13, Jun 29, pp.1-11, 2021.

[43] A. H. Schulman, "Molecular markers to assess genetic diversity," Euphytica, vol. 158, no. 3, pp. 313-321, 2007.

[44] A. Picca, G. Berzero, A. L. Di Stefano, and M. Sanson, "The clinical use of IDH1 and IDH2 mutations in gliomas," Expert Review of Molecular Diagnostics, vol. 18, no. 12, pp. 1041-1051, 2018.

[45] J. B.-K. Hsu et al., "Identification of differentially expressed genes in different glioblastoma regions and their association with Cancer stem cell development and Temozolomide response," Journal of personalized medicine, vol. 11, no. 11, pp. 1047-1055, 2021.

[46] P. Steffen et al., "Protein species as diagnostic markers," (in eng), J Proteomics, vol. 134, pp. 5-18, Feb 1,6 2016.

[47] A. L. Jorge et al., "MicroRNAs: understanding their role in gene expression and cancer," in angerrangerstein (Sao Paulo), vol. 19,pp. 1-7 , 2021.

[48] D. Capper et al., "DNA methylation-based classification of central nervous system tumors," Nature, vol. 555, no. 7697, pp. 469-474, 2018.

[49] I. Khan et al., "Deciphering the role of autophagy in treatment of resistance mechanisms in glioblastoma," International Journal of Molecular Sciences, vol. 22, no. 3, p. 1318, 2021.

[50] L. Salmena, A. Carracedo, and P. P. Pandolfi, "Tenets of PTEN tumor suppression," Cell, vol. 133, no. 3, pp. 403-414, 2008.

[51] E. Schaafsma, E. M. Takacs, S. Kaur, C. Cheng, and M. Kurokawa, "Predicting clinical outcomes of cancer patients with a p53 deficiency gene signature," Scientific reports, vol. 12, no. 1, pp. 1317- 1324, 2022.

[52] J. A. Jalal, A. I. S. Rowandizy, and A. T. Ismael, "Immunohistochemical expression of ATRX in gliomas," Cellular and Molecular Biology, vol. 66, no. 7, pp. 131-135, 2020.

[53] S. Brandner et al., "Diagnostic accuracy of 1p/19q codeletion tests in oligodendroglioma: A comprehensive meta-analysis based on a Cochrane systematic review," Neuropathology and Applied Neurobiology, vol. 48, no. 4, pp. 1-19 , 2022.

[54] "Somatic histone H3 alterations in pediatric diffuse intrinsic pontine gliomas and non-brainstem glioblastomas," Nature genetiGenetics 44, no. 3, pp. 251-253, 2012.

[55] S. Roy et al., "Next-generation sequencing-based molecular characterization of primary urinary bladder adenocarcinoma," Modern Pathology, vol. 30, no. 8, pp. 1133-1143, 2017.

[56] S. Horn et al., "TERT promoter mutations in familial and sporadic melanoma," Science, vol. 339, no. 6122, pp. 959-961, 2013.

[57] F. Sahm et al., "DNA methylation-based classification and grading system for meningioma: a multicentre, retrospective analysis," The lancetLancetogy, vol. 18, no. 5, pp. 682-694, 2017.

[58] M. Zanfardino, K. Pane, P. Mirabelli, M. Salvatore, and M. Franzese, "TCGA-TCIA impact on radiogenomics cancer research: a systematic review," International Journal of Molecular Sciences, vol. 20, no. 23, pp. 6033-6047, 2019.

[59] K. Clark et al., "The Cancer Imaging Archive (TCIA): maintaining and operating a public information repository," Journal of digital digital Imaging 26, pp. 1045-1057, 2013.

[60] L. Weninger, O. Rippel, S. Koppers, and D. Merhof, "Segmentation of brain tumors and patient survival prediction: Methods for the brats 2018 challenge," in Brainlesion: Glioma, Multiple Sclerosis, Stroke and T,raumatic Brain Injuries: 4th International Workshop, BrainLes 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16, 2018, Revised Selected Papers, Part II 4, 2019: Springer, pp. 3-12, 2019.

[61] M. R. Hernandez Petzsche et al., "ISLES 2022: A multi-center magnetic resonance imaging stroke lesion segmentation dataset," Scientific data, vol. 9, no. 1, pp. 762- 771, 2022.

[62] G. Youssef and J. J. Miller, "Lower grade gliomas," Current Neurology and Neuroscience Reports, vol. 20, pp. 1-9, 2020.

[63] C. J. Weber et al., "The worldwide Alzheimer's disease neuroimaging initiative: ADNI-3 updates and global perspectives," Alzheimer's & Dementia: Translational Research & Clinical Interventions, vol. 7, no. 1, pp. 1-9, 2021.

[64] P. A. Rudnick et al., "A description of the clinical proteomic tumor analysis consortium (CPTAC) common data analysis pipeline," Journal of proteome research, vol. 15, no. 3, pp. 1023-1032, 2016.

[65] T. J. Brown et al., "Management of low-grade glioma: a systematic review and meta-analysis," Neuro-oncology practice, vol. 6, no. 4, pp. 249-258, 2019.

[66] J. Ye et al., "Tumor Grade and Overall Survival Prediction of Gliomas Using Radiomics," Scientific Programming, vol. 2021, pp. 1-11, 2021.

[67] V. Y. Borole, S. S. Nimbhore, and D. S. S. Kawthekar, "Image processing techniques for brain tumor detection: A review," International Journal of Emerging Trends & Technology in Computer Science (IJETTCS), vol. 4, no. 5, p. 28-32, 2015.

[68] S. Hussain, S. M. Anwar, and M. Majid, "Brain tumor segmentation using cascaded deep convolutional neural network," in 2017 39th annual International Conference of the IEEE Engineering in medicine aMedicinegy Society (EMBC), 2017: IEEE, pp. 1998-2001, 2017.

[69] A. Bilenia, D. Sharma, H. Raj, R. Raman, and M. Bhattacharya, "Brain tumor segmentation with skull stripping and modified fuzzy C-means," in Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2018, Volume 1, 2019: Springer, pp. 229-237, 2019.

[70] A. Iantsen, V. Jaouen, D. Visvikis, and M. Hatt, "Squeeze-and-excitation normalization for brain tumor segmentation," in Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: 6th International Workshop, BrainLes 2020, Held in Conjunction with MICCAI 2020, Lima, Peru, October 4, 2020, Revised Selected Papers, Part II 6, 2021: Springer, pp. 366-373, 2021.

[71] S. Bobbillapati and A. J. Rani, "Automatic detection of brain tumor through magnetic resonance image," Int J Sci Res Publ, vol. 3, no. 11, pp. 1-5, 2014.

[72] Z. Akkus, A. Galimzianova, A. Hoogi, D. L. Rubin, and B. J. Erickson, "Deep learning for brain MRI segmentation: state of the art and future directions," Journal of digital imaging, vol. 30, pp. 449-459, 2017.

[73] Z. Liu et al., "Deep learning based brain tumor segmentation: a survey," Complex & Intelligent Systems, vol. 9, no. 1, pp. 1001-1026, 2023.

[74] R. Ranjbarzadeh, A. Caputo, E. B. Tirkolaee, S. J. Ghoushchi, and M. Bendechache, "Brain tumor segmentation of MRI images: A comprehensive review on the application of artificial intelligence tools," Computers in Biology and Medicine, p. 106405- 106417, 2022.

[75] K. Kamnitsas et al., "Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation," Medical image analysis, vol. 36, pp. 61-78, 2017.

[76] A. Fawzi, A. Achuthan, and B. Belaton, "Brain image segmentation in recent years: A narrative review," Brain Sciences, vol. 11, no. 8, pp. 1055- 1067, 2021.

[77] J. M. Bhalodiya, S. N. Lim Choi Keung, and T. N. Arvanitis, "Magnetic resonance image-based brain tumor segmentation methods: A systematic review," Digital Health, vol. 8, pp. 1063-1068, 2022.

[78] D. Zikic et al., "Decision forests for tissue-specific segmentation of higher high-grades in multi-channel MR," in MICCAI (3), pp. 369-376, 2012.

[79] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "Deeplab: Semantic image Segmentation with deep convolutional nets, atrous convolution, and fully connected crfs," IEEE Transactions on pattern analysis and machine intelligence, vol. 40, no. 4, pp. 834-848, 2017.

[80] S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz, and D. Terzopoulos, "Image segmentation using deep learning: A survey," IEEE Transactions on pattern analysis and machine intelligence, vol. 44, no. 7, pp. 3523-3542, 2021.

[81] H. Wang, J. W. Suh, S. R. Das, J. B. Pluta, C. Craige, and P. A. Yushkevich, "Multi-atlas Segmentation with joint label fusion," IEEE Transactions on pattern analysis and machine intelligence, vol. 35, no. 3, pp. 611-623, 2012.

[82] H. Dong, G. Yang, F. Liu, Y. Mo, and Y. Guo, "Automatic brain tumor detection and segmentation using U-Net based fully convolutional networks," in Medical Image Understanding and Analysis: 21st Annual Conference, MIUA 2017, Edinburgh, UK, July 11–13, 2017, Proceedings 21, 2017: Springer, pp. 506-517, 2017.

[83] L. Weninger, Q. Liu, and D. Merhof, "Multi-task learning for brain tumor segmentation," in Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traum,atic Brain Injuries: 5th International Workshop, BrainLes 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 17, 2019, Revised Selected Papers, Part I 5, 2020: Springer, pp. 327-337, 2020.

[84] H. Li, A. Li, and M. Wang, "A novel end-to-end brain tumor segmentation method using improved fully convolutional networks," (in eng), Comput Biol Med, vol. 108, pp. 150-160, May 2019.

[85] U. Baid et al., "A novel approach for fully automatic intra-tumor segmentation with 3D U-Net architecture for gliomas," Frontiers in Computational Neuroscience, pp. 10-19, 2020.

[86] A. Prasoon, K. Petersen, C. Igel, F. Lauze, E. Dam, and M. Nielsen, "Deep feature learning for knee cartilage segmentation using a tri-planar Convolutional neural network," in Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013: 16th International Conference, Nagoya, Japan, September 22-26, 2013, Proceedings, Part II 16, 2013: Springer, pp. 246-253, 2013.

[87] S. Chandra et al., Context-aware 3D CNNs for brain tumor segmentation," in Brainlesion: Glioma, Multiple Sclerosis, Stroke, and Traumatic Brain Injuries: 4th International Workshop, BrainLes 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16, 2018, Revised Selected Papers, Part II 4, 2019: Springer, pp. 299-310, 2019.

[88] D. Sun et al., "A comparison of methods to harmonize cortical thickness measurements across scanners and sites," NeuroImage, vol. 261, p. 1-19, 2022.

[89] K. Wang et al., "High fidelity deep learning-based MRI reconstruction with instance-wise discriminative feature matching loss," Magnetic Resonance in Medicine, vol. 88, no. 1, pp. 476-491, 2022.

[90] R. Ranjbarzadeh, A. Bagherian Kasgari, S. Jafarzadeh Ghoushchi, S. Anari, M. Naseri, and M. Bendechache, "Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images," Scientific Reports, vol. 11, no. 1, pp. 1-17, 2021.

[91] A. M. Sarhan, "Brain tumor classification in magnetic resonance images using deep learning and wavelet transform," Journal of Biomedical Science and Engineering, vol. 13, no. 06, pp. 102-112, 2020.

[92] R. Prema, S. Ramya, and B. Thirumahal, "Brain Tumor Detection Using Gray Level Co-Occurrence Matrix Feature Extraction Technique," in Smart Intelligent Computing and Communication Technology: IOS Press, 2021, pp. 580-585, 2021.

[93] J. Ramasamy, R. Doshi, and K. K. Hiran, "Detection of Brain Tumor in Medical Images Based on Feature Extraction by HOG and Machine Learning Algorithms," in 2022 International Conference on

Trends in Quantum Computing and Emerging Business Technologies (TQCEBT), 2022: IEEE, pp. 1-5.

[94] A. Saleh, R. Sukaik, and S. S. Abu-Naser, "Brain tumor classification using deep learning," in 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech), 2020: IEEE, pp. 131-136.

[95] M. Arif, F. Ajesh, S. Shamsudheen, O. Geman, D. Izdrui, and D. Vicoveanu, "Brain tumor detection and classification by MRI using biologically inspired orthogonal wavelet transform and deep learning techniques," Journal of Healthcare Engineering, vol. 2022, pp. 1-18, 2022.

[96] M. Devi and S. Maheswaran, "An efficient method for brain tumor detection using texture features and SVM classifier in MR images," Asian Pacific Journal of Cancer Prevention: APJCP, vol. 19, no. 10, pp. 1-9, 2018.

[97] S. A. Nawaz, D. M. Khan, and S. Qadri, "Brain tumor classification based on hybrid optimized multi-features analysis using magnetic resonance imaging dataset," Applied Artificial Intelligence, vol. 36, no. 1, p. 1-18, 2022.

[98] R. Mostafiz, M. S. Uddin, I. Jabin, M. M. Hossain, and M. M. Rahman, "Automatic Brain Tumor Detection From MRI Using Curvelet Transform and Neural Features," International Journal of Ambient Computing and Intelligence (IJACI), vol. 13, no. 1, pp. 1-18, 2022.

[99] H. Kibriya, M. Masood, M. Nawaz, R. Rafique, and S. Rehman, "Multiclass brain tumor classification using convolutional neural network and support vector machine," in 2021 Mohammad Ali Jinnah University International Conference on Computing (MAJICC), 2021: IEEE, pp. 1-4.

[100] M. Li, L. Kuang, S. Xu, and Z. Sha, "Brain tumor detection based on multimodal information fusion and convolutional neural network," IEEE Access, vol. 7, pp. 180134-180146, 2019.

[101] C. L. Choudhury, C. Mahanty, R. Kumar, and B. K. Mishra, "Brain tumor detection and classification using convolutional neural network and deep neural network," in 2020 International Conference on Computer Science, engineeEngineeringplications (ICCSEA), 2020: IEEE, pp. 1-4.

[102] C. Bhatt, I. Kumar, V. Vijayakumar, K. U. Singh, and A. Kumar, "The state of the art of deep learning models in medical science and their challenges," Multimedia Systems, vol. 27, no. 4, pp. 599-613, 2021.

[103] A. S. Lundervold and A. Lundervold, "An overview of deep learning in medical imaging focusing on MRI," Zeitschrift für Medizinische Physik, vol. 29, no. 2, pp. 102-127, 2019.

[104] M. A. Mazurowski, M. Buda, A. Saha, and M. R. Bashir, "Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI," Journal of magnetic resonance imaging, vol. 49, no. 4, pp. 939-954, 2019.

[105] T. Hollon et al., "Artificial-intelligence-based molecular classification of diffuse gliomas using rapid, label-free optical imaging," Nature Medicine, pp. 1-5, 2023.

[106] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem, "Classification using deep learning neural networks for brain tumors," Future Computing and Informatics Journal, vol. 3, no. 1, pp. 68-71, 2018.

[107] C. N. Ladefoged, L. Marner, A. Hindsholm, I. Law, L. Højgaard, and F. L. Andersen, "Deep learning based attenuation correction of PET/MRI in pediatric brain tumor patients: evaluation in a clinical setting," Frontiers in neuroscience, vol. 12, p. 1-15, 2019.

[108] J. Lao et al., "A deep learning-based radiomics model for prediction of survival in glioblastoma multiforme," Scientific Reports, vol. 7, no. 1, pp. 1-8, 2017.

[109] S. Maqsood, R. Damaševičius, and R. Maskeliūnas, "Multi-modal brain tumor detection using deep neural network and multiclass SVM," Medicina, vol. 58, no. 8, p. 1-10, 2022.

[110] A. Santhosh, T. Saranya, S. Sundar, and S. Natarajan, "Deep Learning Techniques for Brain Tumor Diagnosis: A Review," in 2021 Fourth International Conference on Microelectronics, Signals & Systems (ICMSS), 2021: IEEE, pp. 1-6.

[111] Y. Zhuge et al., "Automated glioma grading on conventional MRI images using deep convolutional neural networks," Medical Physics, vol. 47, no. 7, pp. 3044-3053, 2020.

[112] S. Das, S. Bose, G. K. Nayak, S. C. Satapathy, and S. Saxena, "Brain tumor segmentation and overall survival period prediction in glioblastoma multiforme using radiomic features," Concurrency and Computation: Practice and Experience, vol. 34, no. 20, p. 1-17, 2022.

[113] J. G. SivaSai, P. N. Srinivasu, M. N. Sindhuri, K. Rohitha, and S. Deepika, "An automated segmentation of brain MR image through fuzzy recurrent neural network," in Bio-inspired neurocomputing: Springer, 2020, pp. 163-179.

[114] V. Akila, P. Abhilash, P. B. V. S. Phanindra, J. P. Kumar, and A. Kavitha, "Brain Tumors Classification System Using Convolutional Recurrent Neural Network," in E3S Web of Conferences, 2021, vol. 309: EDP Sciences, pp. 1-5, 2021.

[115] S. F. Ahmed, F. S. Rahman, T. Tabassum, and M. T. I. Bhuiyan, "3D U-Net: Fully Convolutional Neural Network for Automatic Brain Tumor Segmentation," in 2019 22nd International Conference on Computer and Information Technology (ICCIT), 2019: IEEE, pp. 1-6.

[116] A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha, "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture," Microscopy Research and Technique, vol. 84, no. 1, pp. 133-149, 2021.

[117] H. Mzoughi et al., "Deep multi-scale 3D convolutional neural network (CNN) for MRI gliomas brain tumor classification," Journal of Digital Imaging, vol. 33, pp. 903-915, 2020.

[118] Y. Xie et al., "Convolutional neural network techniques for brain tumor classification (from 2015 to 2022): Review, challenges, and future perspectives," Diagnostics, vol. 12, no. 8, pp. 1-8, 2022.

[119] R. Vankdothu, M. A. Hameed, and H. Fatima, "A brain tumor identification and classification using deep learning based on CNN-LSTM method," Computers and Electrical Engineering, vol. 101, pp. 1-18, 2022.

[120] G. S. Tandel et al., "A review on a deep learning perspective in brain cancer classification," Cancers, vol. 11, no. 1, pp. 1-11, 2019.

[121] A. Novozamsky, B. Mahdian, and S. Saic, "IMD2020: A large-scale annotated dataset tailored for detecting manipulated images," in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision Workshops, 2020, pp. 71-80.

[122] S. Masoudi et al., "Quick guide on radiology image pre-processing for deep learning applications in prostate cancer research," Journal of Medical Imaging, vol. 8, no. 1, pp. 010901-010901, 2021.

[123] A. İ. Tekkeşin, "Artificial intelligence in healthcare: past, present and future," Anatol J Cardiol, vol. 22, no. Suppl 2, pp. 8-9, 2019.

[124] S. K. Zhou et al., "A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises," Proceedings of the IEEE, vol. 109, no. 5, pp. 820-838, 2021.

[125] D. Justus, J. Brennan, S. Bonner, and A. S. McGough, "Predicting the computational cost of deep learning models," in 2018 IEEE internaInternational Conference data (Big Data), 2018: IEEE, pp. 3873-3882.

[126] A. Lydia and S. Francis, "A survey of optimization techniques for deep learning networks," International Journal for Research in Engineering Application & Management (IJREAM), vol. 5, no. 02, pp. 1-17, 2019.

[127] M. A. Naser and M. J. Deen, "Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images," Computers in biology and medicine, vol. 121, p. 1-17, 2020.

[128] K. Chang et al., "Automatic assessment of glioma burden: a deep learning algorithm for fully automated volumetric and bidimensional measurement," Neuro-oncology, vol. 21, no. 11, pp. 1412-1422, 2019.

[129] J. Waller et al., "Applications and challenges of artificial intelligence in diagnostic and interventional radiology," Polish Journal of Radiology, vol. 87, no. 1, pp. 113-117, 2022.