Brain Tumor Detection and Screening Using Artificial Intelligence Techniques: Current Trends and Future Perspectives

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Abstract: A brain tumor is an abnormal mass of tissue located inside the skull. In addition to putting pressure on the healthy parts of the brain, it can lead to significant health problems. Depending on the region of the brain tumor, it can cause a wide range of health issues. As malignant brain tumors grow rapidly, the mortality rate of individuals with this cancer can increase substantially with each passing week. Hence it is vital to detect these tumors early so that preventive measures can be taken at the initial stages. Computer-aided diagnosis (CAD) systems, in coordination with artificial intelligence (AI) techniques, have a vital role in the early detection of this disorder. In this review, we studied 119 research articles published from 2000 to 2022. Here, the challenges and status faced by CAD systems based on different modalities are highlighted along with the current requirements of this domain and future prospects in this area of research.

Keywords: *Brain Tumor, Classification, CT, Deep Learning, Machine Learning, MRI, PET, Segmentation.*

1. Introduction

A brain tumor is an uncontrolled growth of cancerous or noncancerous cells inside a rigid skull [1-5] (please refer to Figure 1). It can cause many serious health issues, including death. The mortality rate of any individual suffering from a malignant brain tumor increases rapidly if preventive measures are neglected at the initial stages. The signs and symptoms of a brain tumor vary according to the tumor's location and size. The two classes (benign and malignant) are further divided into several sub-classes and are typically labelled based on tumor location. Meningioma (a benign brain tumor that originates from the meninges), pituitary adenoma (a benign brain tumor that develops from the pituitary gland), schwannoma (formed from Schwan cells that protect and support the nervous system), nasopharyngeal angiofibroma (a benign tumor of the nasopharynx) and many more are examples of benign brain tumors. Among the malignant brain tumors are gliomas (which originate from glial cells that maintain brain and spinal cord functions), ependymal tumors (originating from cells that line the central canal or ventricles of the spinal cord), hemangiopericytomas (tumors that are caused by pericytes within the walls of capillaries) pineal tumors

(tumors that originate within the pineal gland) and metastases of cancers from distant parts of the body [6].

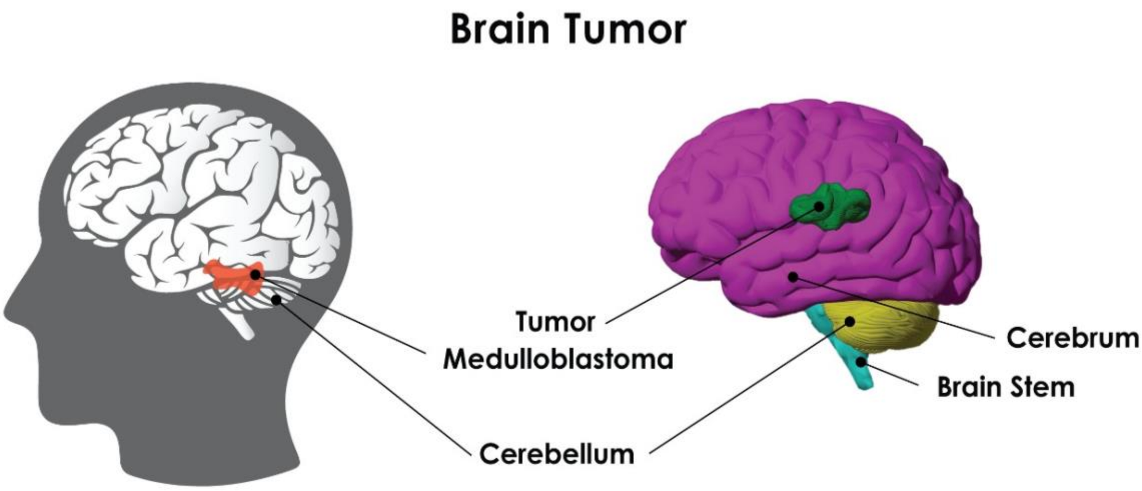

Figure 1. Anatomy of brain and brain tumor.

The location of the brain tumor will affect different body functions. For example, a brain tumor in the cerebellum may affect movement, walking, balance, and coordination [7]. If the tumor exerts pressure on the optic nerve, which is responsible for sight, this could affect vision, such as by causing blurry vision, flashes of light, or increasing blind spots. Symptoms accompanying different types of brain tumors may include headache, seizures, convulsions, forgetting words, a disoriented or confused state in general, and difficulties in locomotion [8].

As the age of a person increases, the possibility of brain cancer also increases [9] and has been observed as being particularly more prevalent in individuals aged 65 and older. There is a variation in the age factor dependent upon cell type and tumor location. It has been observed that the risk of developing medulloblastomas is minimal in adults, but gliomas are common [10]. There is a possible link between genetics and the development of brain tumors, wherein Von Hippel-Lindau disease, Li-Fraumeni syndrome and Neurofibromatosis (NF1 and NF2) are some of the conditions that are inherited. These conditions are normally found in families with a history of rare brain tumors [11].

A 2012 survey carried out by the central brain tumor registry of the united states (CBTRUS) found that brain tumors were the largest cause of related death and the fifth largest cause of death for adults between the ages of 20 and 29. Almost 88,970 people in the US will be diagnosed with brain tumors in 2022, out of which 63,040 will be non-malignant, and 25,930 will be malignant, with the median age at diagnosis being 61 years (Available in https://braintumor.org/brain-tumors/about-brain-tumors/brain-tumor-facts/). It was also predicted that 3540 children under 15 years will be diagnosed with a brain or central nervous system tumor [12]. According to the national brain tumor foundation (NBTF), the number of death in developed countries due to brain tumors has increased by 300% over the past 3 decades [44, 128]; these were classified as either metastatic brain tumors or primary brain tumors. In response to the seriousness of this condition, the world health organization has now developed a grading system for brain tumors, as shown in Table 1.

Table 1: Different grades of a tumor [13].

Grades of a tumor	Details
Grade I	Tumor is slow growing and unlikely to spread. These can be possibly cured through surgery alone.
Grade II	Tumor growth rate is relatively slow and somewhat infiltrative, and there are chances that these may recur as higher grade after treatment.
Grade III	Tumor is fast growing, likely to spread into nearby tissues and tends to recur as higher grade after treatment.
Grade IV	Rapid, aggressive growth of tumor cells, containing both abnormal blood vessel growth and dead tissue. Most malignant and with rapid recurrence.

The effect of brain tumors is such that the years of survival after diagnosis decreases as the tumor grade increases over time. Hence, detecting malignant brain tumors early is imperative to improve treatment efficacy and outcome. The first step that needs to be taken to start the detection process is brain imaging. There are several brain imaging techniques. They are positron emission tomography (PET), magnetic resonance imaging (MRI), magnetic resonance spectroscopy (MRS), computed tomography (CT), and single-photon emission computed tomography (SPECT). Brain scans, including CT and MRI, are used to confirm tumors and the degree of malignancy since obtaining biopsies is time-consuming in the case of a brain tumor. Out of these options, MRI, which uses radiofrequency signals with a strong magnetic field for human tissue imaging, is the most frequently used method. This is because it can provide detailed information related to the size, type of brain tumor, and shape. The second step in the process is to use artificial intelligence (AI) techniques for the automated detection of complex patterns and abnormal tissues in brain scans.

With the high number of brain cancer cases and deaths each year, there has been a rise in research interest in the automatic detection of brain tumors [14]. This paper reviews all articles on computer-aided diagnostic (CAD) systems developed for the automated detection of brain tumors published from 2000 to 2022. The primary intention of CAD relating to this topic is to help the clinician identify the exact location, type and severity of the tumor formed in the human brain over a period of time. We have investigated the most popular modalities used in the proposed CAD systems, and the most reliable and frequently used datasets for research purposes. The main steps used in these CAD systems are preprocessing, segmentation, feature extraction and Deep layer methods. Detailed discussions on the methodologies and classifiers used in the CAD systems are included in this review. The comparison of our review paper with other state-of-the-art review papers is shown in Figure 2. It can be noted from the figure that our review-discussed papers are related to all imaging modalities and artificial intelligence techniques.

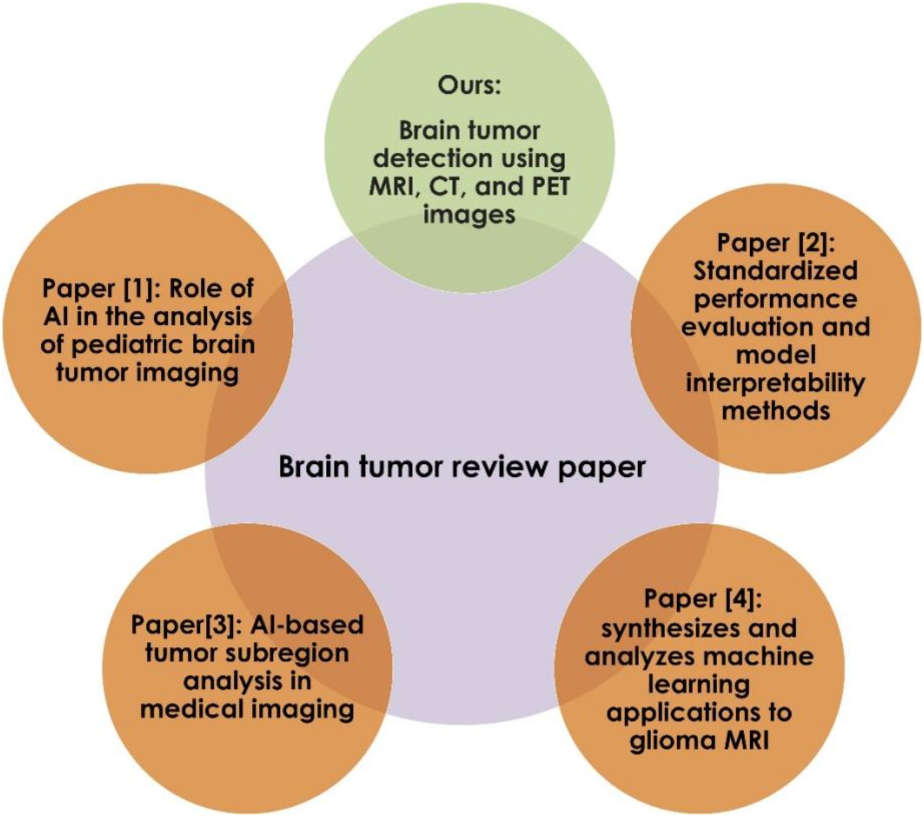

Figure 2: Comparison of review papers published related to this work.

The main contribution of the paper is as follows.

- To develop gaps in current research, a total of 119 papers are critically reviewed with various imaging modalities to automatically detect brain tumours.
- We select best computerized identification method of brain tumors which includes statistical, machine learning (ML), deep learning (DL), and hybrid methods, analyzed with a diverse range of performance parameters.
- We present future directions of research tailored for new researchers to investigate brain tumor detection analysis in a sophisticated manner.
- We finally provide insights into brain tumor detection and screening, particularly based on artificial intelligence techniques including the current trends and future perspectives for both emerging and well-established researchers.

2. Review Objective

In this study, the methodology from the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statements [15] was adopted. From our extensive search of the literature, it can be observed that NIH-based studies are more medically intensive, however, this study is mainly focused on the algorithms which are needed to automate the detection of brain tumors. Hence, we have considered Springer, Science Direct, Wiley, and IEEE Xplore as these are widely available repositories in areas of algorithms for brain tumors and related research works. Hence, the search process was carried out using keywords or related subfields on the search engines: Springer, Science Direct, Wiley and IEEE Xplore. The following keywords were used: 'Brain Tumor', 'CAD System', 'Malignant Brain Tumor', 'AI in Brain Tumor Detection', 'ML in Brain Tumor Detection', 'Statistical Image Processing', 'Supervised Learning', 'Un-supervised Learning', 'Brain tumor in deep learning', 'Brain tumor Detection Using Deep Learning', 'Brain Lesions Detection Using Deep Learning' and 'Brain tumor Detection Using Vision Transformers'. Relevant articles published from 2000 to 2022 in English related to the study were downloaded. A total of 272 articles were collected, not limited by region or country. Sixty-two articles were removed due to duplication and irrelevance. The screening was carried out in 2 phases: i) Phase I: based on the title and abstract, ii) Phase II: based on modality, methodology, and technical aspects. Finally, a total of 119 papers were gathered for further analysis. Figure 3 shows the complete selection process for the articles. To the best of the authors' knowledge, this study has considered all relevant articles published to identify brain tumors using machine learning and deep learning techniques.

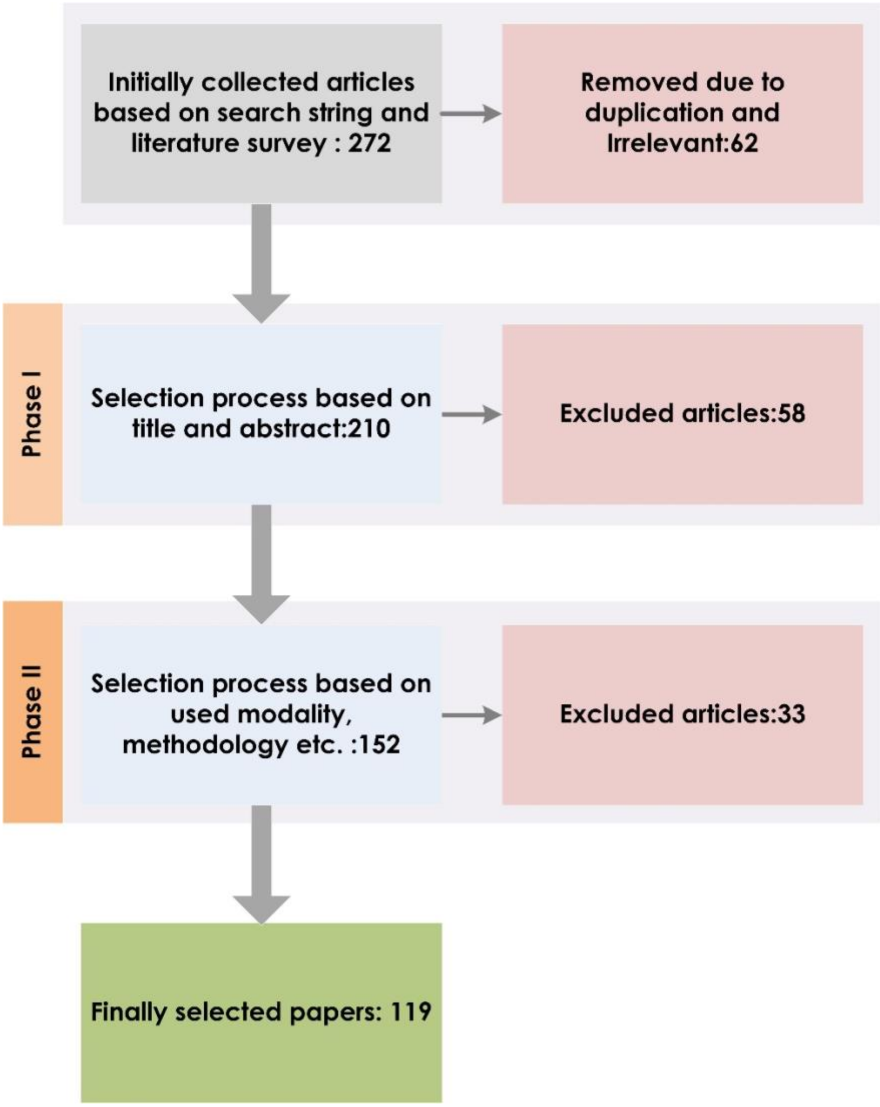

Figure 3. PRISMA architecture used for the selection of research articles.

3. Brain Tumor Imaging

3.1 Modality

The first step for tumor detection using a CAD system is to collect brain scans or images. There are several modalities used for non-invasive brain scanning. The most popular modalities are MRI, PET, CT and Xray, where each has its own advantages and disadvantages The MRI technique is a major advancement in the field of medical imaging. MRI plays a key role because it can provide structural, microstructural, functional, and metabolic information [16]. This technique also prevents patients from being exposed to potentially harmful ionizing radiation. There are two types of MRI imagery: T1-weighted and T2-weighted images. The anatomy and pathology of the brain are often represented by T1- and T2-weighted images, respectively [17].

The PET imaging technique involves detecting two time-coincident high-energy photons released from a positron-emitting radioisotope that emits two photons at the same time It may be noted that PET is the same as PETCT. It also offers significant information to study brain tissues [18]. In the case of a CT scan, a series of X-ray images that are taken from different angles are combined. Thereafter, we utilize computer processing to create cross-sectional images (slices) of the body parts, including soft tissues, bones, and blood vessels inside the body. The information provided by CT scans are more detailed when compared to X-rays [19]. It is well known that radiation exposure is a major concern associated with the widespread use of CT scans [20]. In Figure 4, we show the modalities and the architecture for our review process. It is observed that the automated CAD system is categorized into *three* methods: statistical and image processing, ML, and DL. These methods require MRI, CT, and PET images as input. Further, these are analyzed using various methods such as expectation-maximization (EM), Markov random field (MRF), supervised, unsupervised, etc.

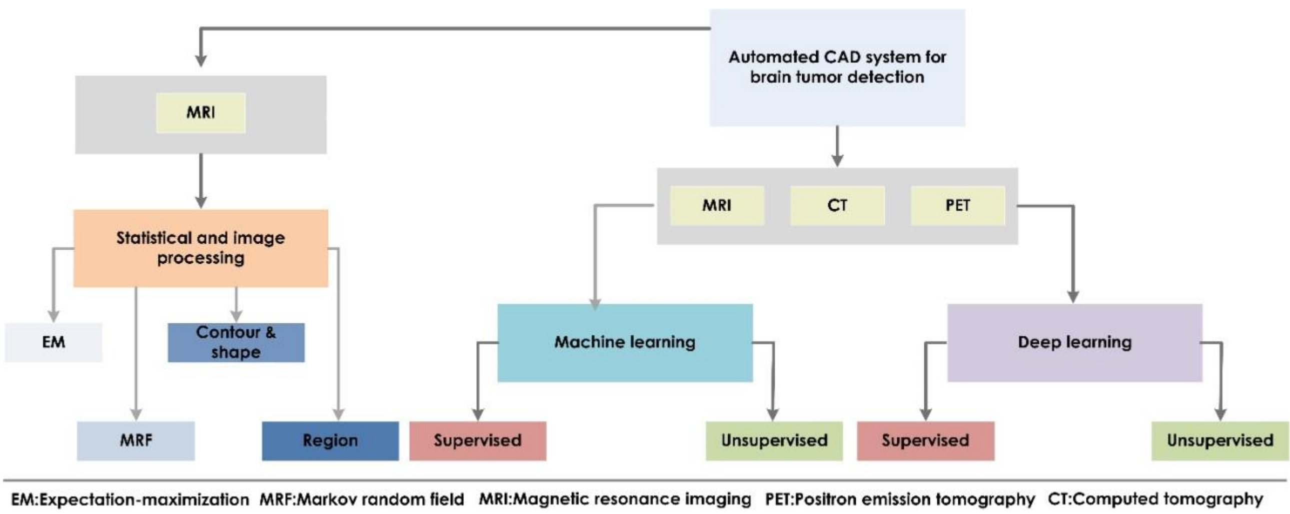

Figure 4. The architecture of the proposed review process for this work.

3.2 Dataset

The most popular datasets used for research in this field are The Harvard whole brain atlas database, the brain tumor segmentation (BRATS) database, the reference image database to evaluate the therapy response (RIDER) dataset and the dataset from Figshare (available in "https://figshare.com/articles/dataset/brain_tumor_dataset/1512427"). These datasets have been extensively used for research in this domain, and many benchmarks are present for these datasets [21]. Figure 5 shows sample images from the different modalities (available at http://www.med.harvard.edu/aanlib/, and PET images are collected from Kasturba Medical College, Manipal, India).

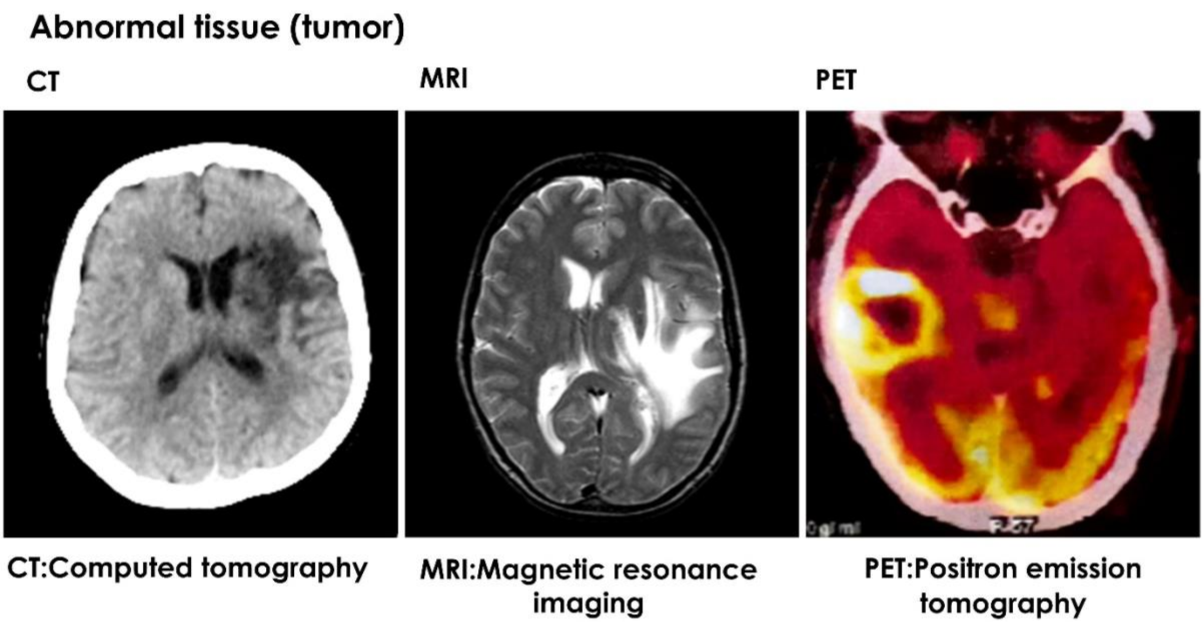

Figure 5. Sample brain tumor images from various modalities.

4. Statistical, Morphological and Clustering Based Segmentation Techniques.

Several statistical-based segmentation (SBS) techniques have been employed to detect tumors and classify them. Donso et al. have proposed a brain tumor segmentation algorithm that is based on the expectation maximization (ETM) approach and found this method to be more efficient because the number of modifications did not significantly increase the complexity of the process. Using the ETM algorithm, the lowest rate of false negative results and standard deviation were obtained [22]. Similarly, Balafar MA proposed an algorithm using ETM with a method designed to overcome the problem of the standard EM algorithm in the presence of image noise [23]. Scherrer et al. proposed an algorithm that uses a Markov random field. Their approach minimized the need for *a priori* knowledge and time computation [24]. It used a local approach to adjust the intensity non-infirmity, dynamically update anatomical relations to work with structured segmentation, and use a multi-agent-based implementation for performing distributed problem-solving. The model also introduced natural dependencies for model regularization [24]. Ramasamy et al. proposed an algorithm that uses the fast Fourier transform (FFT) based on the expectation-maximization Gaussian mixture model (EM-GMM). In their proposed algorithm, the FFT was executed before the EM-GMM algorithm was applied for segmentation. A convolution was performed in the frequency domain instead of the spatial domain, which provided faster image smoothing while maintaining high accuracy [25].

Image processing-based techniques were also popular for the accurate and automated detection of brain tumors. Tang et al. used thresholding and edge-based techniques for their study. Different segmentation techniques - multi-resolution edge detection, automatic intensity thresholding and region selection methods were employed. Their segmentation method combined regional image information and image intensity information. It also combined image filtering and region-growing [26]. Somasundaram et al. implemented a brain extraction algorithm that is fully automatic for axial T2-weighted MRIs using a thresholding technique. In the study, two algorithms were developed - 2D-BEA and 3D-BEA. Neither of these algorithms requires any initial parameters from the user. Their algorithms worked well on both normal and abnormal types of T2-weighted images [27]. Jafari et al. proposed a model that will detect brain tissues automatically from MRI modality employing the Seed-Region Growing technique for segmenting the region of interest (ROI) and Artificial neural networks classification [28].

Rajendran et al. executed an algorithm that used a deformable model and fuzzy clustering to perform tumor segmentation on supplied MRI brain imagery. The deformable model was made by combining a region-based fuzzy clustering method. This method is called enhanced possibilistic fuzzy C-means (EPFCM) and is a boundary-based method. The results provided by this model were quantitatively verified and outperformed other models [29]. Dubey et al. introduced a semi-automatic segmentation of MRI brain tumors that used the level-set technique [30]. Siyal et al. proposed an algorithm based on an intelligent modified fuzzy C-means (FCM) model. This proposed method is used for estimating bias and segmenting brain MRI. Also developed was a modified FCM algorithm that can automatically segment and perform intensity correction of MR imagery [31]. Rajan et al., proposed a novel neural network-based classifier that was developed to distinguish between malignant and benign brain tumors in MRI imagery. The algorithm utilized six steps to provide an output- preprocessing, first automatic seeded region growing for segmentation, then connected component labelling was performed and after that feature extraction was done, then feature dimension reduction was performed, and finally, classification took place [34]. Studies with optimization techniques for improvements in the results are mentioned in the literature [32,33,35-37]. Details of the various image processing-based articles are presented in Table 2.

Table 2: Statistical based, Morphology and clustering-based tumor detection techniques.

Article	Modality	Database	Methodology/Classifier		Result
Melissa L. Bondy et al., [7] (2010)	***	Central Brain Tumor Registry of the US (CBTRUS), SEER	Statistical	Conditional logical Regression	Risk factor was found higher in Gliomas
Donoso et al.,[22] (2010)	MRI	Private dataset	Statistical	ETM	**Acc**: 99.96%
MA Balafar.[23] (2011)	MRI	https://brainweb.bic.mni.mcgill.ca/brainweb/	Statistical	GMM+EM	EM similarity index-0.8211
Scherrer et al.,[24] (2009)	MRI	BrainWeb phantom.	Statistical	Markov random field (LOCUS-T)	**DCC** obtained for different sub-volume sizes on the 5% noise, 40% inhomogeneity BrainWeb phantom.
Ramasamy et al.,[25] (2011)	MRI	Private dataset	Statistical based segmentation technique	FFT+EM+GMM	**Acc**: 98 % -0.01 noise level 93%- 0.10 noise level

H. Tang et al.,[26] (2000)	MRI	Private dataset	Region-based segmentation technique	Thresholding, edge-based	reduced noise in homogeneous regions but preserves fine structures of the brain
Somasundaram et al.,[27] (2010)	MRI	Harvard, KGS Advanced MR, and private dataset	Region-based segmentation technique	Thresholding	Similarity percentage using The **Jacc** is above 80% (Slice thickness 1mm and above)
Jafari et al.,[28] (2011)	MRI	Harvard	Region-based segmentation technique	Seed Region	1) BPNN- normal and abnormal **Sen**: 100% **Spec**: 98% 2)BPNN- abnormal image to benign or malignant with **Sen**:99.5% **Spec**: 96%
A. Rajendran et al.,[29] (2011)	MRI	Private dataset	Contour & shape-based segmentation technique	Fuzzy C+ Deformable model+ EPFCM	**SI** > 70% avg **FPVF**- 1.06% avg **FNVF**- 0.98%.
Dubey et al.,[30] (2009)	MRI	Private dataset	Contour & shape-based segmentation technique	Level set snake	Agreement % Dataset 1- 99.51% Dataset 2- 93.97%

Siyal et al., [31] (2005)	MRI	BrainWeb		FCM	Misclassification rate and segmentation 0%-INH-0.0354% 40%-INH-0.0376%

****Acc: Accuracy, Sen: Sensitivity, Spec: Specificity, DCC: Dice Coefficient, DCS: Dice Coefficient Score, SI: Similarity Index, Jacc: Jaccard Index FPVF: False positive volume function, FNVF: False negative volume function**

5. Machine learning-based technique

ML is a subset of AI that can be trained and used to accurately predict outcomes and it is one of the most popular techniques for automating CAD systems. Ortiza et al. proposed a supervised artificial neural network (ANN) methodology to improve the segmentation of MRI images [38]. Their proposed segmentation method uses hybrid artificial intelligence techniques to improve segmentation accuracy. Three issues were addressed in their paper– the feature extraction process, the use of an effective classifier that groups the voxels which belong to a specific class, and finally, a method that selects the features which will be provided as input to the classifier [38]. Abdalla et al. proposed a supervised ML technique for brain tumor detection. Their proposed algorithm was successful in implementing the model, which extracted features from brain MRI images. The extracted features in the method were calculated using equations of Haralick's features. These features are based on the spatial gray level dependency (SGLD) matrix of images. The classification of the photos with or without tumors is done using a neural network. [39].

Zacharaki et al. developed an algorithm using a combination of conventional and perfusion MRI coupled with a support vector machine (SVM) for differential tumor diagnosis. The developed classification scheme achieved high accuracy for most of the classification problems. The method used a statistical feature and Gabor texture for feature extraction [40]. Weili et al. developed an algorithm with unsupervised machine learning employing the pulse-coupled neural network (PCNN) technique for medical image segmentation. The suggested method improved the chargeable threshold function in PCNN and combined 2D Tsallis entropy to segment the image automatically. The resulting segmented images had stronger adaptability and better precision [41].

Amin et al. proposed a method that automates the preprocessing, feature extraction and classification (using SVM) of MRI images [42]. Chen et al. suggested a method for the automatic diagnosis and segmentation of brain tumors based on the gray-level co-occurrence matrix (GLCM) for feature extraction and employing an extended Kalman filter with the SVM as a classifier. The method presented here achieved an accuracy of 98.02% [43]. Sayed et al. proposed a new algorithm that uses the discrete wavelet transform (DWT) and principal component analysis (PCA) for feature detection and the feedback PCNN (FPCNN) as a classifier. The proposed process was easy to operate, non-invasive, inexpensive, rapid, and achieved an accuracy of 99% [44]. Many studies showcase superior results obtained through hybrid ML techniques, either through the fusion of image features or through the extracted features [45-52]. Song et al. extracted features and fed them to the neural network with an extended set-membership filter to perform image classification [53]. Along similar lines, many ML-based studies have been conducted based on unique feature identification [54-62]. Hybrid classifiers enjoy the best of both individual techniques, producing potentially better results [63-71]. The classifiers such as SVM, random forest (RF), multi-layer perceptron (MLP), K nearest neighbor (KNN), linear discriminant analysis (LDA), back propagation neural network (BPNN), probabilistic neural network (PNN), etc., are extensively used in ML techniques. The studies combined the spatial features extracted from convolution with classification performed by simple ML techniques. The details of various machine learning-based articles are presented in Table 3.

Table 3: Machine learning based tumor detection technique.

Article	Modality	Database	Feature Extraction	Segmentation Method/ Classifier	Result
Martinez et al.,[33] (2019)	HIS	Vivo Human Brain Cancer Database	Genetic algorithm (GA)	SVM	Improved **Acc** by ~ 5%
Rajan et al.,[34] (2019)	MRI		Clustering	SVM	**Acc** - 99.43%
Basha et al.,[35] (2021)	MRI	TCGA-GBM dataset, Figshare & Rembrandt repository	Convolutional neural network (CNN) + enhanced Harris Hawks algorithm		**Acc** - 97.7%
Ortiz et al., [36] (2013)	MRI	IBSR1.0 database	First order + Second order + Invariant features	Growing hierarchical self-organizing map (SOM)	***
Vishnuvarthanan et al. [37] (2016)	MRI	Harvard Brain Web Repository, Private dataset	FCM + SOM		**Acc**- 96.18%
Ortiza et al.,[38] (2013)	MRI	IBSR and IBSR 2.0 databases	GA	HFS-SOM, EGS-SOM	Result is in the Tanimoto performance index

Abdalla et al.,[39] (2018)	MRI	Harvard	Harlick's features	ANN	**Acc**: 99% **Sen**: 97.92%
Zacharaki et al.,[40] (2009)	MRI	Private dataset	Statistical features+ Gabor texture	SVM	**Acc**- 90.9%
Weili et al.,[41] (2009)	MRI	Private dataset	PCNN+ Tsallis entropy		***
Amin et al.,[42] (2017)	MRI	Private dataset, Harvard, RIDER	Texture+ shape+ intensity-based features using GLCM	SVM	**Acc**: 97.1%, **AUC**: 0.98, **Sen**: 91.9%, **Spec**: 98.0%
Chen et al.,[43] (2021)	MRI	Private Dataset	GLCM	EKF-SVM	**Acc**: 98.02%, **Spec**: 95.39% **Sen: -** 97.04%
Sayed et al.,[44] (2014)	MRI	Harvard	DWT+PCA	FPCNN	**Acc** - 99%, **Spec**: 92.8%,**Sen**:100 %

Abdel-Maksoud et al.,[45] (2015)	MRI	DICOM, Brain Web data set, BraTS	K-means integrated with FCM (KIFCM) + Thresholding segmentation+ Level set		**Acc** -100% **Prec**- 100%, **Rec**- 100%
Grist et al.,[46]	MRI	Private dataset	Various ML algorithms used		>80 % **Prec** is achieved
Lu et al.,[47] (2018)	MRI	The Cancer Imaging Archive	Statistical analysis	SVM + Ensemble learning	**Acc** -96.1% **Sen**- 95.7% **Spec**- 100%
Agrawal et al.,[48] (2018)	CT	Brain Web, DICOM	k-means segmentation+ Sobel edge detection + Morphological processing.		**Acc** - 95%
Al-Saffar et al., [49] (2021)	MRI	TCIA (The Cancer Imaging Archive)	Multiple Eigenvalues selection scheme	SVM and MLP	**Acc** (MES + MLP)-90.03% (MES + SVM)-91.02%
Amin et al.,[50] (2018)	MRI	BraTS 2012,2013, ISLES 2014,2015	Fusing various features	RF	**Acc** BraTS 2012- 98.9 %, ISLES 2015- 93.3
Oksüz et al., [51] (2022)	MRI	J. Cheng, brain tumor dataset, Figshare, 2017; LGG-1p19q Deletion data set	Deep features + Shallow features	SVM, KNN	**Acc** SVM-97.25% KNN-97%
Jahan et al., [52] (2021)	MRI	Private dataset	Extract central moments (Mean, Variance and Standard deviation)	ANN	**Acc** -92.17%

Song et al.,[53] (2021)	MRI	Private dataset	GLCM	BPNN+ Extended set-membership filter	**Acc** - 97.14%
Huang et al.,[54] (2014)	MRI	MICCAI 2012 and 2013, BraTS 2012	Local independent projection-based classification (LIPC)		Avg Dice Similarities Complete tumor- 0.84, Tumor core- 0.685, Contrast-enhancing tumor- 0.585
Budati et al.,[55] (2021)	MRI	BraTS 2017, Harvard	Chan-Vese technique + GLCM	KNN, SVM	**Acc** SVM- 98.13% KNN-92.3%
Cinarer et al.,[56] (2019)	MRI	TCIA, TCGA	N/a+ multifocal+ multicentric+ gliomatosis features	SVM, KNN, LDA & RF	**Acc** SVM-90% KNN-87% LDA-83% RF-83%
Shafi et al.,[57] (2021)	MRI	Figshare	GLCM, Gray-level run length matrix, Gray-level size zone matrix, Neighborhood	SVM	**Acc** -97.957%

			gray-tone difference matrix		
Deb et al.,[58] (2020)	MRI	BraTS	GLCM	Adaptive fuzzy deep neural network + Frog Leap Optimization + adaptive flying squirrel algorithm + Shannon's' function	**Acc** - 99.6%
Sharma et al.,[61] (2018)	MRI	Private dataset	SIFT (shape, color intensity)	SVR	**Acc** - 80.97705%
Citak-Er et al.,[62] (2018)	MRI	Private dataset	SVM + MLP + Logistic regression		**Acc** - 93.0% **Spec**- 86.7% **Sen**- 96.4%
Zacharaki et al.,[63] (2009)	MRI	Private dataset	Shape, intensity and texture features + SVM-recursive feature elimination	SVM	**Acc** - 85% **Sen**-87% **Spec**- 79%
Kibriya et al.,[64] (2021)	MRI	Publicly available Figshare dataset	CNN	SVM	**Acc** -98%
Kumar et al.,[65] (2020)	MRI	BraTS, SimBraTS	Local directional pattern + statistical features	Deep CNN	**Acc** -96.3%
Sharif et al.,[66] (2018)	MRI	Harvard database, Private dataset	GLCM+ Haralick features + GA	SVM	**Acc** -99.69%
		BRATS 2015		RF, ANN & SVM	

Joshi et al.,[67]	MRI		Image filtering-based features		Detection Rate RF-92%, ANN-90%, SVM-88%
Shinde et al.,[68] (2018)	MRI	BraTS 2015	Logistic Regression		Correctly Classified Instances - 90%
Kang et al.,[69] (2021)	MRI	BT- large- 4C	CNN+ SVM		**Acc** - 93.72%
Shree et al.,[71] (2018)	MRI	www.diacom.com and test dataset	GLCM+ DWT	PNN	**Acc** -98%
AUC: Area Under the Curve, Prec: Precision, Rec: Recall					

6. Deep learning-based methods

DL is a subset of AI that attempts to imitate the human brain and works as a connected network of neurons. DL is one of the most popular and advanced methods used for unsupervised learning. Here, the goal is to develop a fully automated CAD system to detect tumors from brain images. Heba et al. used a 7-fold cross-validation technique for building and training the 7 hidden layer structures. To increase the performance of the training results, they incorporated another machine learning algorithm termed WEKA, using the same criteria. The classification used KNN, initialized with K=1 and N=3. The proposed methodology by the researchers included image segmentation by FCM, feature extraction by the DWT, and the PCA method for reduction [72]. Soumick et al. incorporated spatiotemporal models for video classification. Hence the potential of their model in classifying 3D volumetric MRI images. Spatiotemporal models like residual networks (ResNet) (2+1) D and ResNet mixed convolutions were utilized in the network for training the model. The models were trained using PyTorch and were compared with and without pre-training. The performance of the models and the classification grades of the brain tumors were improved [73].

Developments in high-speed computing and novel DL-based approaches and models present novel opportunities for preventing and maintaining several neurological illnesses. Aklima et al. [74] discussed the current approaches to developing various neurological disorder systems. They discussed various preprocessing methods (such as histogram normalization, intensity normalization, filtering, etc.) and feature extraction methods (such as discrete cosine transform, linear discriminant analysis, etc.) for detecting neurological disorders. Chenji et al. utilized two different datasets to evaluate the glioma classification independently, namely, Glioma grading and Molecular based subtype classification. The suggested method was able to obtain high overall performance. The suggested semi-supervised strategy achieved equivalent performance to fully supervised ones, compared to results with numerous state-of-the-art approaches [75]. Ahmed et al. highlighted some recent work that attempted to classify tumors using MR imaging but encountered problems due to the huge bulk data used and inaccurate prediction/classification models. They proposed a structured solution to overcome this, including deep learning models with feature extraction and several classification models to categorize the MRI images of gliomas and meningiomas, and pituitary tumors incorporating different augmentation techniques [76]. Samani et al. showed that extracellular water differences between infiltrative tissue and vasogenic edema could be used to train a convolutional neural network model (CNN) on the free water volume fraction obtained from diffusion tensor imaging (DTI). The CNN could distinguish between primary and secondary cancers in a cross-validation situation of differentiating extracellular water changes between local patches in the peritumoral area of 66 glioblastomas and brain metastases.

The authors in reference [76] used majority voting on patches on an independent test cohort composed of ten metastases and twenty glioblastomas and distinguished them with 93% accuracy. They achieved a precision higher than any other CNN-trained model, which uses conventional DTI-based measurements. Some of the commonly used DTI-based measurements are mean diffusivity (MD) and fractional anisotropy (FA), which were used for other investigations [77]. Ahuja et al. attempted to automatically classify, locate, and segment brain cancers from T1W-CE MRI datasets. The 8:1:1 T1W-CE MRI dataset was split into a training set of 80%, a validation set- of 10% and a testing set of 10%. The geometrical techniques and a 2-level wavelet decomposition were used to enhance the training data set to alleviate overfitting difficulties (scaling, rotation, translation). For the brain tumor localization and multi-class classification, the efficacy of the pre-trained DarkNet model (DarkNet-19 and DarkNet-53) was assessed. The top-performing pre-trained DarkNet model obtained 98.81% accuracy during validation and 99.60% accuracy during training. The suggested approach was applied to MRI images from the BraTS 2018 dataset to show the superiority of the proposed method. The comparative analysis of performance evaluation parameters of the proposed methodology with a highly self-sufficient technique demonstrates its robustness and clinical significance [78]. Transfer learning studies [79-83] showcase that learning inculcated in the underlying task performs much better than models trained from scratch. Menze et al. enlist the multimodal brain tumor image segmentation benchmarks [84]. Recent DL-based techniques have been mentioned in [85-123]. The details of various deep learning-based articles are presented in Table 4. Figure 6 depicts the range of accuracies for all the collective techniques surveyed in this study. Figure 7 shows the range of accuracies for all techniques using a boxplot.

Table 4: Deep learning-based segmentation techniques.

Article	Modality	Database	Methodology	Result
Heba et al., (2018) [72]	MRI	Harvard medical school website	Deep neural Networks (DNN)	DNN:- Classification rate – 96.97 **Rec**– 0.97, **Prec**– 0.97, **AUC** – 0.984
Soumick et al., (2022) [73]	MRI	BraTS 2019	ResNet (2+1)D + ResNet mixed convolutions	**F1Sc** – 0.9345 **Acc** – 96.98
Aklima Akter Lima et al., (2022) [74]	Electroencephalogram (EEG)	Bonn time series database, Temple University EEG corpus	CAD Transfer Learning, Deep feature fusion	Generative adversarial network (GAN):- **Acc** – 94.1% RF:- **Acc** – 98.3%
Ahmed M. Gab Allah et al., (2021) [76]	MRI, X-RAYS	Public dataset of 3064 T1-CE MR images	VGG16 + CNN VGG19 + GRU VGG19 + Bi – GRU VGG19+BI-GRU With Progressive Growing GANS	RMSProp = 98.54
Samani et al., (2021) [77]	MRI	Bulk patient data	2D CNN	CNN:- **Acc-** 85%, **Sen** = 87%, **Spec** = 81
Ahuja et al., (2022) [78]	MRI	Figshare dataset	Transfer learning (DarkNet model)	**Acc** – 99.43%, **Sen** – 98.84%, **Spec** – 99.60%

Deniz Kavi et al., (2021) [80]	MRI	N. Chakrabarty, "Brain MRI Images for Brain Tumor Detection",2021, Cheng, J. (2017, April 2). "Brain tumor dataset".	CNN+ Residual Network + Transfer Learning (ResNet50)	**Acc** -99.26%
Hirahara et al., (2019) [81]	MRI	Kaggle	Transfer learning (Xception model)	**Acc**:- Normal – 96.13% Tumor – 99.99%
Zahoor et al., [82] (2022)	MRI	Kaggle, CE-MRI Figshare	Dynamic features brain region-edge net (BRAIN-RENet)	**Acc:-** DBFS-ES-99.56%
Rehman et al., [83] (2020)	MRI	Figshare	Pretrained Nets with SVM	**Acc:-** 98.69% test set, 98.79% on the validation set, and 99.02% on the training set
Pei - ju- Chao et al.,(2022). [86]	MRI, CT	Cerebral Edema Dataset by Chung Gung Memorial Hospital	R-CNN	**DCC**- 0.88, **IoU** - 0.79 **VOE** - 2.0
Tahereh Mahmoudi et al., (2022) [88]	MRI, CT	NIH dataset	U-Net, Attention U-Net	**Sen** – 0.95 **Spec** – 0.94 **Acc** – 0.95
Hao Dong et al., (2017) [89]	MRI	BraTS 2015	U-Net-based deep convolutional networks	**DCC**:- Core = 0.86
Zheshu Jia et al., (2020) [91]	MRI	Bulk dataset	Fully automatic heterogenous segmentation (FAHS-SVM)	FAHS-SVM probability ratio – 98.8
Siqui zhang et al., (2021) [92]	CT	Private dataset	Deep learning	**DCS**:- Small lesions – 0.61 Larger lesions – 0.81

Fangzhou Xu et al., (2021) [93]	Motor imagery (MI)	EEG dataset	EEG Net architecture	**Acc** – 75%
Yoon-A Choi et al., (2021) [94]	MRI/CT	EEG dataset	Deep learning	CNN-LSTM:- **Sen** – 94.0% **Spec** – 94.3% **Acc** – 81.4%
Kambiz nael et al., (2021) [95]	MRI	15,811 MRI dataset	3D neural networks	**AUC**– 91% **Sen** – 83% **Spec** – 86% (for Normal vs abnormal MRI)
He Huang et al.,(2021) [96]	MRI	BraTS 2019, 2018, 2020	Deep learning using V-Net	**DCS** – 76
Manan Noor et al.,(2020)[97]	CT, PET, MRI	ADNI, OASIS, COBRE, FBIRN	Deep learning, CNN, DNN	**Acc** – 0.9059 **Spec** – 0.9176 **Sen** – 0.9296
Havaei et al., (2017) [98]	MRI	BraTS 2013	DNN	**Dice-** 0.88 **Spec-** 0.89 **Sen-** 0.87
Fang Liu et al., (2018) [99]	MRI, PET	Bulk datasets from patients	MRAC (MR-imaging-based attenuation correction), Convolution Auto - Encoder	**DCS** – 0.971
Ilyasse et al., (2021) [100]	MRI, CT	BraTS 2017	CNN	Training-: **Acc** – 98 Validation-: **Acc** – 91

Waqas Nadeem et al., (2020) [101]	MRI, CT	BraTS 2017	Fully CNNs and Conditional Random Fields	-
Tirivangani magadza et al., (2021) [102]	MRI, CT, PET	BraTS, MICCAI	Deep learning	Cascaded **Sen** – 0.915 segNet **Spec** – 0.997
Christian federau et al., (2020) [103]	DWI	Stroke database of 962 cases (ISLES, ImageNet)	Deep learning 3D U-net	Mean dice score – 0.72 **Sen** – 85% **Spec** – 48%
Ramin et al., (2021) [104]	MRI	BraTS 2018	Deep learning, CNN, C-CNN, ConvNet	**DSC** – 0.8726(core) **Sen** – 0.9712(core)
Chandhan Ganesh et al., (2020) [105]	MRI, DICOM images	BraTS 2017, 2018	3D dense net	BraTS 2018:- **DCC**– 0.92 **Sen** – 0.91
Linmin Pei et al., (2020) [106]	MRI	BraTS 2019, 2020, TCIA	CAENeT, ResNet, U-Net, UNet-VAE	**DCC**–0.749(validation)
Pawel et al., (2019) [107]	MRI, CT	BraTS 2018	CNN-based segmentation model, 3D U-NET	Whole tumor:- Mixed supervision(30 FA + 198 WA) – 81.23
Theo Estienne et al., (2020) [108]	MRI	BraTS 2018, OASIS 3	DL methods	**DSC** – 1(WT, CT, ET)
Francisco Javier et al., (2021) [109]	MRI, CT, PET, SPECT, MRS	Nanfang hospital, Tianjing medical university	Multi – pathway CNN	**DCC**– 0.828(avg) **Sen** – 0.940(avg)

Todd Hollon et al., (2020) [110]	H&E images	2.5 million Stimulated Raman Histology (SRH) images	CNN	**Acc**: 94.6
Chandan Ganesh et al., (2020) [111]	MRI	TCIA, TCGA	Dense U-Nets	**Acc** – 97.14 **Sen** – 0.97+- 0.03 **Spec** – 0.98+- 0.01
Ruquian Hao et al., (2021) [112]	MRI	BraTS 2019	Transfer learning	**AUC** :- Validation set – 86.86
Ellah et al.,(2018) [113]	MRI	BrasTs 2013	CNN-SVM	**Acc:- 99.55%**

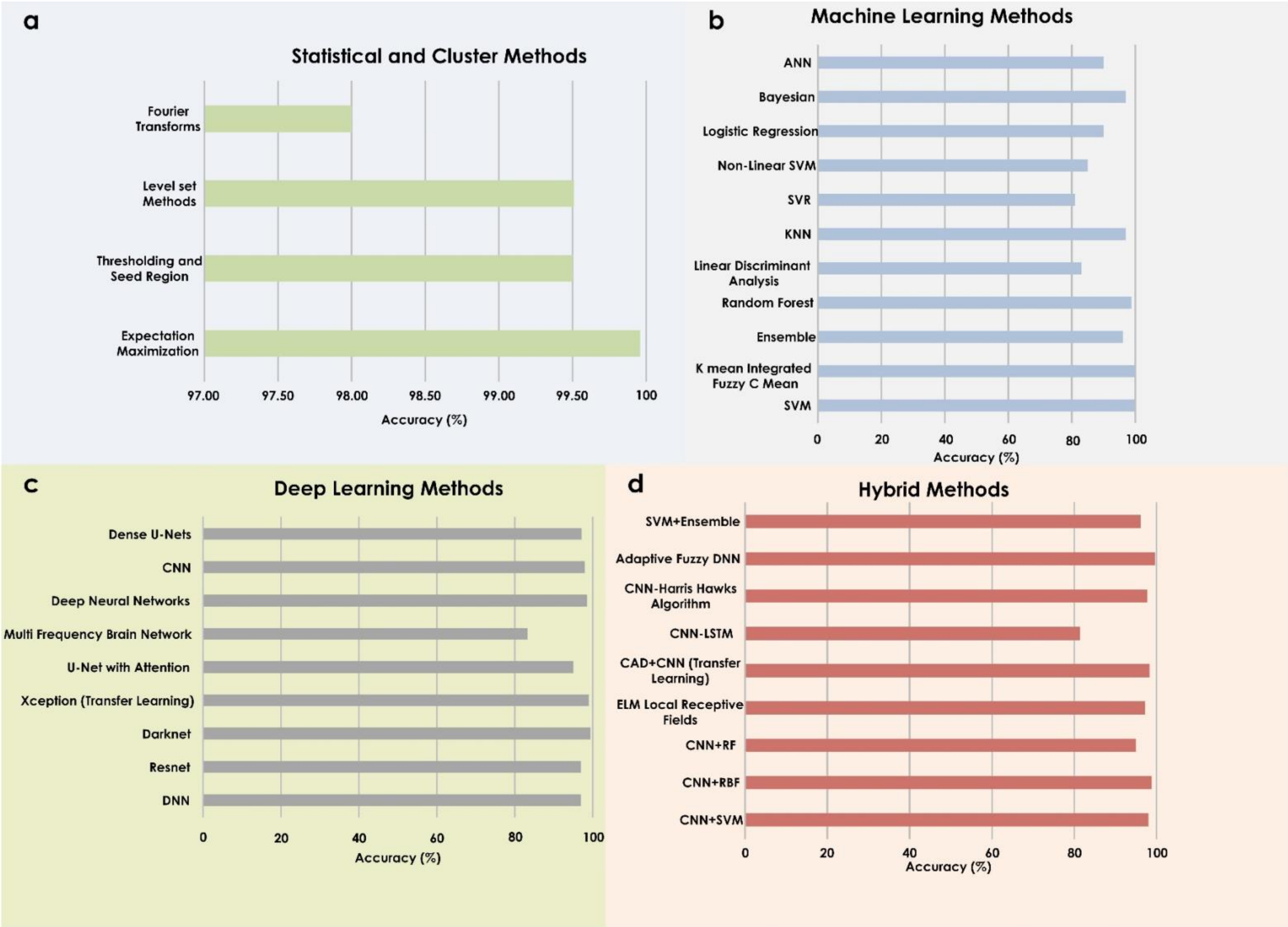

Figure 6. Accuracies of various methods segregated by technique.

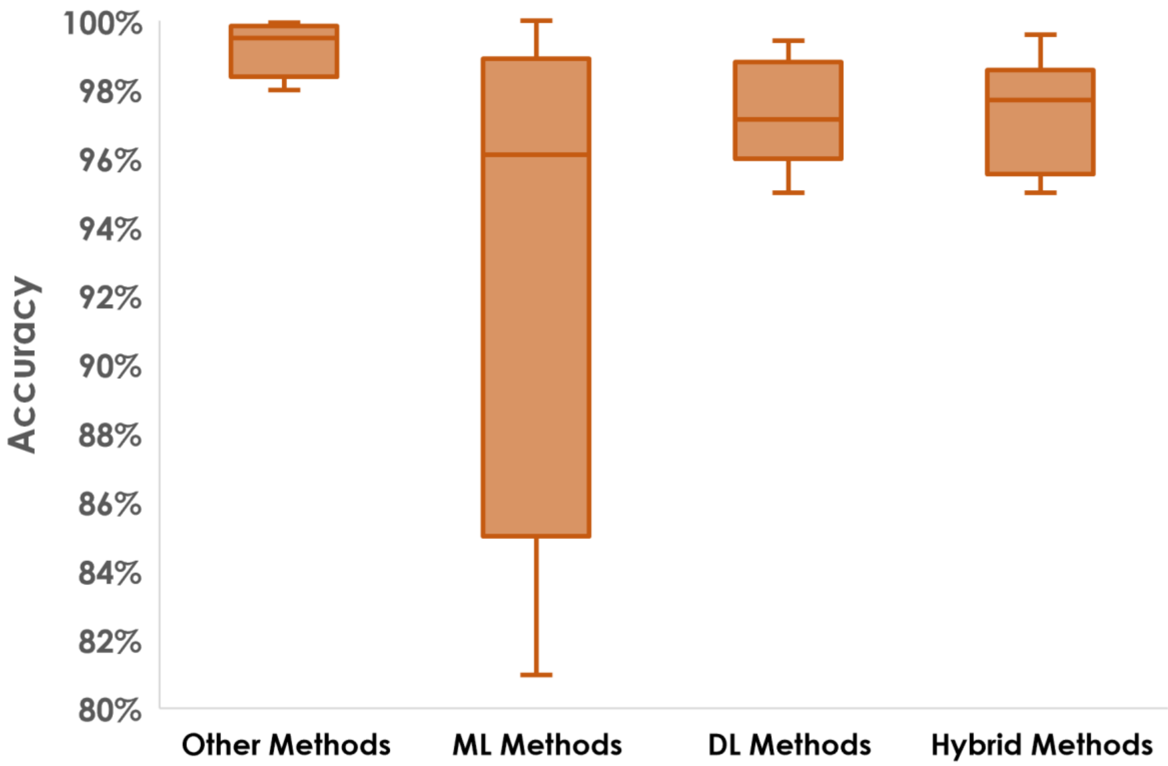

Figure 7. Boxplot of the accuracies of various methods.

7. Discussion

This section discusses the most important methodologies and techniques used in this field, along with the challenges of current systems and the future scope for automated brain tumor detection.

7.1.Non-ML/DL-based techniques

One of the most popular techniques used in non-ML/ DL techniques is the SBS technique. There are many types of classifiers used in this technique, each with distinct advantages and disadvantages. The modified EM technique is able to overcome the presence of noise in the image and estimate the mixture model parameters. However, it is less flexible in the spatial relationship dependences modelling, and future improvements include incorporating the bias field estimation that corrects or compensates for the intensity inhomogeneities introduced during the acquisition of MRI.

The Markov random field is another popular classifier under the SBS techniques. This method is not deterministic, and its statistical properties are its best characteristic. However, it can only be used to detect sufficiently homogenous tumors so that they can be segregated and added to only one normal tissue class. This is why it cannot be employed to segment heterogeneous tumors. It allows us to recognize tumor forms that have usual intensities but are too dense to qualify as normal. [44].

The GMM is also a popular classifier under the guise of SBS techniques. One can readily implement GMM, and the number of parameters required is less. One more advantage is that by adopting the EM algorithm, these parameters can be efficiently estimated so that the log-likelihood function can be maximized. The spatial relationships between adjacent pixels in the GMM are not taken into account, and the model assumes that each pixel is unperturbed of its neighbors. This is a problem.

In conclusion, image processing-based segmentation should not be overlooked. There are several classifiers included in this method, including thresholding, seed regions, deformable models, and level sets. The thresholding technique is particularly useful in situations where image linearization is required since it is performed during segmentation. Nevertheless, this method cannot be applied to all types of MRI segmentation problems with large variations in the intensity of foreground and background images. Deformable models are another method for contracting and expanding different shapes in an image over time and also confirming specific image features. However, this method may present problems in noisy images with unclear boundaries. There may be shapes with topologies that are inconsistent with those of the object being studied due to this. There is also the possibility of segmentation using level sets. This technique is widely used in medical imaging, as it can handle a wide range of parameters and scenarios, including cavities, concavities, convolutions, splitting, and merging.

7.2.Machine Learning based techniques

ML is one of the most fundamental methods used to develop systems for the automated detection of brain tumors. In addition, machine learning is used for pattern recognition and segmentation in the medical imaging field. The ML-based techniques can be broadly classified into supervised and unsupervised learning.

In supervised ML for medical images, an algorithm is trained on labelled images or data. Some of the main supervised machine learning techniques include ANN and SVM. An ANN works well in complicated multivariate, nonlinear medical imaging domains, where using a decision tree or other rule-based systems is not possible. It is also observed that the ML algorithm provides better results in datasets with noisy conditions. Therefore, there is no requirement to assume a basic data allocation. ANN, however, is not without flaws. The model needs to be trained with numerous patient-specific labelled images to build a working ML algorithm, which is an intensive and time-consuming process. The SVM is another supervised ML technique that has a high generalization performance. This is useful when we have extremely high dimensions of the feature space, but training time is long in this approach, and it requires patient-specific learning with large data storage requirements.

The algorithm in unsupervised ML is trained from unlabeled datasets or images. ML can discover hidden patterns or data groupings without requiring human intervention. Some of the main classifiers under the heading of unsupervised machine learning are FCM, SOM, and PCNN. FCM is the most widely used unsupervised clustering technique for segmenting brain tumors from MRIs. However, the main drawback of this method is that it requires significant computation time and it is sensitive to initial cluster centers. In the case of SOM, training an algorithm is easier and faster. This method is very useful and is used as an effective software tool for visualizing high-dimensional data, and this method can automatically detect patterns and features from images. The main disadvantage of this approach is the requirement that the number of neural units in the competitive layer matches the intended number of regions in the picture after segmentation. The produced temporal signal of the PCNN is not affected by the dilation, rotation, or scaling of the images, which is a considerable benefit. In order to generate features and identify patterns in classification tasks using traditional neural networks or other techniques, PCNN is employed in the system. One of the biggest drawbacks of this method is that no method would instantly halt the PCNN algorithm. [44].

After an exhaustive review of the articles in this field, it is concluded that SVM is the most used classifier under the ML techniques. Researchers were able to obtain high accuracy in detecting brain tumors with SVM. A novel classifier termed the Feature Manipulation Engine (FME) is of interest to ML technology. This software platform performs data integration and compiles multiple functions to enable transformation, data integration, processing and validation. These techniques have a wide scope and can be further explored in future works.

7.3.Deep Learning based techniques

The DL techniques have opened up new avenues for research in a variety of fields. Particularly in the medical field, the emergence of DL research and its use in the area is increasing. Many algorithms are being developed to enhance existing systems. There are international competitions to find new DL techniques for tumor detection. The algorithms are evaluated for accuracy, specificity, sensitivity, etc., with the trend being to improve previous efforts. The CNN network architectures are constructed in such a way that they can self-effort to produce better results. The CNN networks, such as U-Nets, ResNets, and many others, have proven to be more efficient [5]. Their ability to be customized as needed and to elucidate in regard to how the feature extraction should work is commendable. Their adaptability to accept modifications in the network to enable the best possible outcome is remarkable. The ROI in CNN architectures is determined by kernel size, which has an impact on diagnostic performance. However, the accuracy of using the CNN architecture for segmenting tumor areas is limited. CNN architectures benefit from the hardware's ability to take advantage of parallelization, with kernel size determining the ROI. Changes to kernel size affect diagnostic performance and can be limited by small kernels missing specific regions or bigger kernels' continued reliance on large parametrization. As a result, most available datasets are grouped in one (unbalanced) category, which can cause overfitting. These issues can be resolved by applying precision and recall based on an objective function that also performs data fusion, especially when GAN techniques (validated for both shape and intensity variation) are proposed for the development of artificial datasets [8]. Hence, detailed and further research should be extended in this direction. The deep learning algorithms employed by researchers have proven to be very effective in classifying tumors accurately, thus making it possible to detect them under any given condition. Some of the most frequently implemented and prevalent classifiers include the DNN, CNN, ANN, and Bayesian classifiers. CNN and Bayesian methods are widely adopted for tumor classification because of their accuracy and preciseness. The main advantages of using CNN are the minimal level of supervision needed, that it can detect the classes on its own, and that it is faster and more efficient than recurrent neural networks (RNN), where the redundancy is truncated. The reason Bayesian classification is widespread is because of its simplicity [80]. It can accept continuous and discrete data and has high scalability in terms of predictors and data points.

It is observed from Tables 2, 3, and 4 that, in the present study, approximately 18%, 41%, and 41% of the work belongs to other methods (such as statistical, clustering, etc.), ML methods, and DL methods respectively. We have considered hybrid techniques in ML-based techniques, and they performed remarkably well. Figures 6 and 7 are plotted based on the method which has achieved maximum accuracy. These plots show that all the methods have exhibited promising results. However, hybrid methods can be explored by combining ML and DL methods to obtain high performances.

7.4.Recent developments

Transformers have become state-of-the-art in natural language processing and a technique applied in vision research [124]. Vision Transformers (ViT) have proven to be superior to CNN in terms of performance and effectiveness. Li et al. [125] proposed a novel transformer which is capable of extracting long-range correlations among different positions of the scan. Tummala et al. [126] employed an ensemble of three transformers for detection and classification. Pinaya et al. [127] combined the feature representations of a variational autoencoder with autoregressive transformers for fast and economical detection. Li Z et al. [128] experimented with histopathological images for primary brain tumors based on weakly supervised Vision Transformers.

7.5. Sample size and execution environment

In the previous related work, two types of datasets were used, publicly available and private datasets. One of the most popular publicly available data sets used is the BraTS data set, which is updated every year. In the BraTS 2020 dataset, there were 369 training, 125 validations, and 169 test multi-modal brain MRI studies. The BraTS 2019 dataset consisted of 259 high-grade gliomas (HGG) and 76 low-grade gliomas (LGG) MRI scans, while the BraTS 2018 challenge training dataset consisted of 210 HGG and 75 LGG scans. The Brain Web dataset consists of 152 images that are used by Abdel-Maksoud et al. [45]. Al-Saffar et al. [49] have used 1467 (axial plane) MR images of 160 patients from the TCIA data set and they have used an Intel R core i7-4500U of CPU 2.40 GHz with 16 GB of RAM. Lu et al. [47] have collected the image data of 456 subjects with gliomas from The Cancer Imaging Archive. In [42] they proposed a ML and SVM-based method and used 3 datasets for their study. They obtained 85 images with ground truth annotation from Nashtar Hospital Multan in which 46 images show evidence of tumor and 39 images are of healthy patients. Here, the Harvard dataset is also used, consisting of 100 images in which 65 images contain tumors and 35 are of healthy tissue. Another dataset used here is The Cancer imaging archive (TCIA) organized RIDER brain image data that consists of 126 patients, in which each case per patient comprises multiple studies. In their research [44], they suggested a tumor identification method utilizing ML, and studies were conducted using 101 pictures from a human brain MRI dataset, comprising of 87 aberrant (malignant and benign tumors) and 14 normal images. The training was carried out using a mix of the wavelet, PCNN, and neural network toolboxes running on the CPU 2.2 GHz, with 3 GB of RAM.

It is also observed that the proposed models that use Deep learning can use larger datasets for training and testing. Kumar et al. [65] have proposed an optimization-driven deep CNN for brain tumor classification. Here, two data sets are employed. The BraTS dataset includes 65 (MRI) pictures of various modalities of that which few (51) images were produced by patients with high-grade gliomas. SimBRATS is another dataset that is utilized; it consists of 50 simulated pictures, of which 25 are of good quality while the other 25 are of low quality. The approach is implemented in MATLAB, and the system environment consists of an Intel CPU 2.16 GHz processor with 2GB RAM. Using a public dataset of 3064 T1-CE MR images and a data set of 3064 T1-CE MR pictures from 233 individuals who had one of three distinct forms of brain tumors, including gliomas (1426 images), meningiomas (708 images), and pituitary tumors, Allah et al. [76] presented a DL-based technique (930 images). The hardware utilized for this study included a graphics processing unit (GPU) P100, 2 TB of storage, and 12 GB of Memory. In their publication, Zahoor et al. [82] introduced a deep hybrid boosted & ensemble learning-based analysis of brain tumors utilizing MRI scans. To carry out their experiment, the scientists gathered 5058 photos, including 3064 photographs of tumors and 1994 images of healthy people. The simulations were run on a Core-I, i7-7500 CPU at 2.90 GHz with a Nvidia® GTX-1060 Tesla that supports CUDA. The suggested model's computing cost was 5-7 hours, with training taking 20–30 minutes for each epoch.

It is very difficult to conclude which method is best for detecting brain tumors, as various methods were executed on different platforms using various datasets. Hence there is a need for an exhaustive dataset with a multicentric study, so researchers can test their algorithms on the fly using a public leaderboard.

7.6. The preferred choice for diagnostic imaging

According to the research articles reviewed, imaging techniques used in this field were not uniform. The three imaging techniques primarily utilized were CT, MRI, and PET. These three methods use different technologies to obtain images of internal organs; each has its advantages and drawbacks. The imaging technique chosen is based on the severity of symptoms and the location of the tumor. MRI is the most common imaging technique used in brain tumor research. This is because tumor detection in MRI is more efficient since it has sharp contrast and sufficient spatial resolution. PET scans, on the other hand, can provide a detailed view of complex systemic diseases and it is, however, more expensive. In terms of accessibility and affordability, a CT scan is preferred over the other two techniques. Thus, there is a requirement to develop a new hybrid medical imaging technique that combines the advantages of each of the existing methods and that also increases accessibility [133].

8. Challenges and Future Discussion

In this survey, we have reviewed several of the most relevant articles on automated brain tumor detection using different methodologies and algorithms. Many algorithms use supervised or unsupervised techniques and can achieve a high accuracy rate for brain tumor detection. However, there is a lack of fully automated procedures. In multiple studies, we found it difficult to compare the results of these outputs, as the final output was given in different parameters and units. It would be helpful and convenient if standard parameters and measures were utilized to assess the results produced by various systems in the future. While searching for articles related to the field, we observed that many studies now use Deep learning for automated tumor detection. We also found that many articles did not mention the data set used to test their proposed algorithm nor provide documentation of the data sets used. Providing information on these data sets would encourage further research and enable future researchers to compare their work easily. Although some success has been achieved in automated tumor detection, there is much scope for developing a system that can assess the state and condition of the tumor.

8.1.Further research can be directed toward several outcomes:

1. *Pinpoint accuracy of CAD systems*: Accuracy in the field of medical imaging is crucial. A minute error in the tumor measurement process can result in life-threatening consequences. Therefore, to improve the treatment of brain tumors and minimize the spread of abnormal cells into surrounding tissues and other organs, we need to improve the accuracy of the medical imaging systems continuously.
2. *Creation of appropriate hardware to execute the CAD algorithms*: The medical imaging algorithm relies heavily on the hardware used during the scanning process. There is a huge scope for developing simplified and cost-effective CAD systems. With the development of these systems, it will be possible to provide accurate and easy-to-use diagnostics in rural areas where medical facilities are underdeveloped. This will assist in preserving numerous lives by enabling early tumor detection.
3. *IOT (Internet of Things) connected and tumor assessment systems*: Besides producing CAD systems with high accuracy, it would be helpful to develop a system that, along with tumor detection, will be able to assess and judge the stage and condition of the detected tumor. Next-generation IoT applications can also be used in this paradigm so that the images and the data collected in rural areas can be accessed at developed medical facilities for properly handling and treating critically ill patients.
4. *There is a huge scope for development in this field using Vision Transformers*. ViT-based solutions have been recently proposed to resolve the issue of long-range dependency in CNN. ViT is a self-attention mechanism that has the capacity to model long-range dependencies, which plays a key role in precise brain tumor segmentation [124].

5. *Medical image analysis usually relies on GAN when producing synthetic data for better training and to avoid overfitting*. Of late, many different domain-inspired techniques have achieved prominence. Models like diffusion models and variations auto-encoders could be explored to produce the data and to check their viability.
6. *Explainable AI (XAI).* XAI helps to boost the confidence of researchers and clinicians in automated detection systems developed using AI techniques. It aids in understanding the working of AI models and is widely used in healthcare systems. Among the others, the more generally used XAI methods are shapley additive explanations (SHAP), gradient-weighted class activation mapping (GradCAM), and local interpretable model agnostic explanations (LIME) [129]. In principle, SHAP is usually used with a random forest or XGboost classifier to perform predictions. It aims to explain the most contributing clinical features for disease prediction. GradCAM, on the other hand, is widely used for medical images to provide heatmaps (visual explanations) highlighting the regions of interest.
7. *Uncertainty.* In any predictive modelling task, it is crucial to detect the reliability of the proposed AI model as such a model is prone to noise, so the tuning parameters of the model may need to be changed to obtain the same high performance in the real-world scenario. Bayesian networks, Demspter-Shafer theory and Fuzzy logic techniques are widely used to make accurate decisions under uncertainty [130]. Uncertainty quantification (UQ) helps to quantify the uncertainty due to deep learning models or data [131,132]. This UQ can be used to mitigate the problem due to data or models in clinical settings.

9. Conclusion

This study examines the trends, status, future direction, and prospects of automated CAD systems for detecting brain tumors. Medical imaging plays a key role in diagnosing brain tumors, and early detection increases the chance of effective treatment and recovery. Obtaining the correct diagnosis and identification by type of brain tumor requires the expertise of experienced radiologists and physicians. A lack of experienced staff in remote or less-developed regions makes it difficult to diagnose brain tumors. With the help of AI, such as ML and DL, further advancements in diagnosing brain tumors can be done. We have put forward several suggestions for improving the accuracy and convenience of automated CAD systems. First, we can develop a new segmentation technique that can be automated and personalized for individual patients. Second, we have observed that there are many different data sets present. We can build a more heterogeneous data set from the collection of data from trusted sources, which can be used to train a robust model that can be implemented for tumor segregation and segmentation. Third, we can create a new modality that combines the strengths of different techniques in use and brings uniformity to the medical imaging segment, which will also help to organize and train an AI-based model with images of similar types. Next, there is a possibility of building a more reliable and accurate imaging device that will decrease the noise and interference in the system, as these factors affect the accuracy of the prediction.

In addition, we can suggest the development of an automated CAD system that can concurrently detect a tumor, define the type of tumor, i.e., malignant or non-malignant, and reveal the grade (stage) of the tumor. Further screening techniques should be combined for an accurate and rapid diagnosis of neurological ailments. Lastly, we can suggest that there is a need for a remote treatment system, where the test and diagnosis of a patient in a rural area can be monitored from a central hub with experienced and highly qualified doctors. This network will help preserve lives, as it will be helpful for the improvement of treatment procedures.

Conflicts of Interest: The authors declare no conflict of interest.

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APPENDIX

Table A1: Abbreviations of Major terms

Abbreviations	**Definitions**
AI	Artificial intelligence
ANN	Artificial neural network
BPNN	Back propagation neural network
BRATS	Brain tumor segmentation
CAD	Computer aided diagnostic
CNN	Convolution neural network
CT	Computed tomography
CVS	Chan-Vese technique
DL	Deep learning
DNN	Dense neural network
DWT	Discrete wavelet transform
EM	Expectation maximization
EM-GMM.	Expectation-Maximization Gaussian Mixture Model
EPFCM	Enhanced possibilistic fuzzy C-means
ESMF	extended set-membership filter

FA	Fractional anisotropy
FCM	Fuzzy C-means
FFT	Fast Fourier transform
FME	Feature Manipulation Engine
FPCNN	Feedback pulse-coupled neural network
GA	Genetic algorithm
GAN	Generative adversarial networks
GLCM	Gray level co-occurrence matrix
GPU	Graphics processing unit
GradCAM	Gradient-weighted class activation mapping
IOT	Internet of Things
ISLES	Ischemic Stroke Lesion Segmentation
KNN	K nearest neighbor
LIME	Local interpretable modelagnostic explanations
MD	Mean diffusivity
MICCAI	Medical Image Computing and Computer Assisted Intervention Society
ML	Machine learning
MLP	Multi-layer perceptron
MRI	Magnetic resonance imaging
MRS	Magnetic resonance spectroscopy
PCA	Principal component analysis
PCNN	Pulse coupled neural network
PET	Positron emission tomography
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
ResNet	Residual Networks
RF	Random Forest
RIDER	Reference image database to evaluate therapy response
ROI	region of interest
SBS	Statistical based segmentation
SGLD	Spatial gray level dependency
SHAP	Shapley Additive exPlanations
SVM	Support vector machine
TCIA	Cancer imaging archive
UQ	Uncertainty quantification
ViT	Vision transformer
ViT	Vision Transformers
XAI	Explainable AI