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A Systematic Literature Review on Classification of Brain Tumor Detection

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Abstract: A tumor is a bloating or irregular growth caused by uncontrolled and unorganized cell division. Brain tumors are a hazardous type of tumor. Tumors in the brain are categorized into a few grades based on their severity. The grade, type, and position of the tumor determines the procedure of medical treatment for brain tumors. Tumors could be life-threatening if not discovered and properly treated at the initial stage. Professionals and doctors use magnetic resonance imaging images to detect brain tumors. Correctness accuracy is dependent on these experts' perceptions and specialized knowledge, and it is also tedious and expensive procedure. Multiple deep learning algorithms were proposed to identify the presence of tumors. However, these techniques have their own limitations and drawbacks. This work offers a thorough understanding of brain tumor detection, focusing primarily on its segmentation and classification by comparing and summarizing the most recent study work in this field. To the best of our knowledge, this is the only comprehensive study on classification of brain tumor detection using deep learning, machine learning and artificial intelligence models in recent literature.

Keywords: classification, deep learning, machine learning.

1. Introduction

Our brain is the center of all nervous operations and the most important and sensitive body part. Brain issues are considered the most difficult to solve. Every year, approximately thirty-five thousand new cases of tumors are diagnosed worldwide, and the survival rate for them is only 36% [1]. The World Health Organization WHO classifies tumors into four grades based on the tumor's characteristics and behavior. The grade of a brain tumor is an important factor in determining the good treatment and predicting the results of the disease Figure 1 [2].

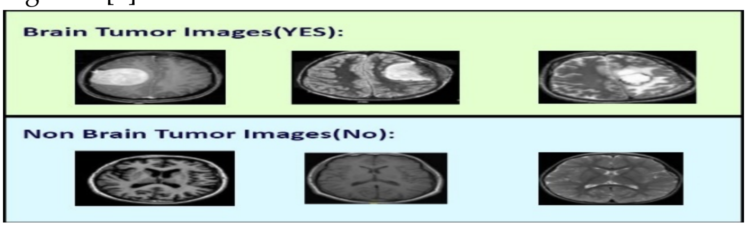

Figure 1. Brain tumors and non-tumors images.

Neurosurgeons frequently asked for surgery to cure the tumors. Alternative approaches, such as radiation and chemotherapy, are frequently recommended for the most advanced stages of tumors. The only possible treatment is to try to remove or control the increasing factor of cancerous cells. Because brain tumors have a high mortality rate, so detecting tumors in their early stages is critical for proper treatment [3].

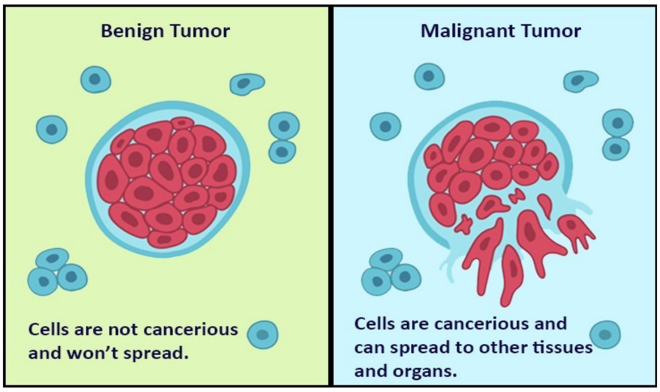

Figure 2. Difference between Benign and Malignant tumor.

Brain tumors can be malignant or benign Figure 2. Primary tumors can be either benign or malignant. Secondary tumors are almost always cancerous. A tumor that is raised in the membranes that line the skeleton and spinal column, is called meninges [4]. However, their development may influence the brain, resulting in disorders such as poor vision, hearing loss, memory lapses, and even muscle spasms. Meningioma cases rise with age, so the symptoms show slowly over time. Meningiomas are typically benign, thus doctors may decide to drop asymptomatic situations by themselves. Doctors will evict the tumor or treat it with radiotherapy if it starts interfering with everyday life. Severe migraines are the typical early signs of cancer [5].

For medical testing, images from various medical imaging techniques can be obtained. Techniques for images include positron emission tomography, MRI, and computed tomography [6]. The most efficient medical imaging technique, specifically for studying the nervous system, is magnetic resonance imaging [7].

2. Deep Learning and Machine Learning Techniques

Medical imaging and healthcare experts complement one another in numerous ways. Radiologists and physicians usually are highly versatile, as well as can better negotiate with patients while explaining and exchanging their findings along with treatment options. They observe a patient through medical history, and symptoms presenting typical and atypical cases. However, to cut down the diagnosis time, maintain accuracy, and to minimize the risk of human errors radiologists and healthcare assistants must incorporate Computer Aided Systems (CAD). Through CAD experts can easily compare a patient's record with other similar cases and make a more precise and reproducible history. Simultaneous diagnosis reports by different radiologists can also be compared and integrated to maintain and keep track of the changes in a patient's record over the span of time.

- Supervised machine learning algorithms accurately predict behavior by utilizing labeled examples to apply what they have learned in the past to fresh data. After analyzing a defined training example, the algorithm creates a technique that can be used to estimate output values [8]. The system can provide benchmarks for new input after sufficient training. In addition, the program can find faults to enhance the model by comparing its results to the desired results.
- Unsupervised machine learning algorithms are applied When training data are not categorized or tagged [8]. It studies how systems can imply performance from unidentified data to explain their underlying pattern. The device does not detect the exact results, but rather uncovers the information and can make inferences from the data sets to explain the nameless data's buried structures.
- Semi-supervised machine learning algorithms are a hybrid of unsupervised and supervised in which Unlabeled and heterogeneous data are also used for learning, with a substantial part of unlabeled data and little labeled data commonly used. This technique can greatly increase accuracy in systems [8]. When training/learning from labeled acquired, data necessitates the use of skilled and relevant resources, semi-supervised learning is typically chosen. Otherwise, obtaining unidentified data does not usually necessitate extra resource use.

Reinforcement Machine learning algorithms are a type of technique that engages with its surroundings by performing specified tasks and spotting mistakes or incentives. Pursuit of late reward, error, trial, and the key components of learning reinforcement [8]. With this technique, both hardware and software entities can choose the most appropriate behavior in each perspective to improve success. Concise compensation notes are needed so that the agent can choose the optimal approach; It's called a boost message. Massive amounts of data can be analyzed using machine learning [9].

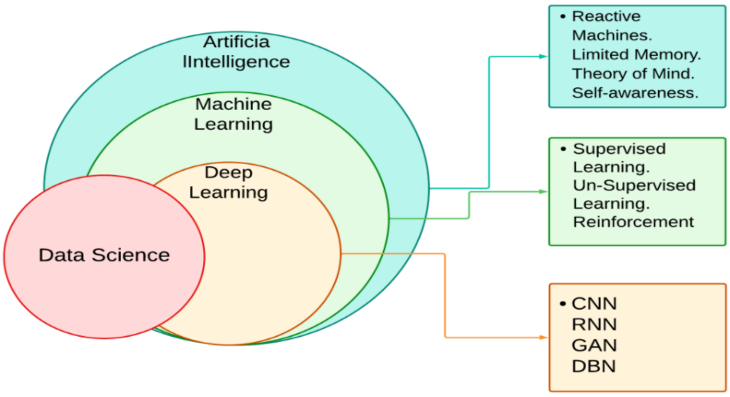

Figure 3. Relationship between AI, DL, ML Techniques

This paper categorized the recent survey papers into classes such as deep learning, machine learning, artificial intelligence, and neural networks that use pre-trained approaches such as Xception, ResNet50, MobileNet, Inception-v3, and VGG-16, among others Figure 3. This work offers a thorough understanding of brain tumor detection, focusing primarily on its segmentation and classification by comparing and summarizing the most recent study work in this field. To the best of our knowledge, this is the only comprehensive study on classification of brain tumor detection using deep learning, machine learning and artificial intelligence models in recent literature.

The purpose of this review article is to demonstrate the benefits of a deep learning framework for analyzing a novel, multi-step brain disease detection method. Section II of this article presents a review of recent techniques. Section III presents the performance review and related topics. The debate, conclusion, and future scope are in Section IV.

3. Taxonomy of Brain Tumor Detection Models

Medical imaging techniques are used to create images of the human body's organs for diagnosis. A brain tumor is a dangerous disorder that can change your life. Image segmentation is important for image processing because it makes it easier to isolate questionable areas from medical images. Deep learning, machine learning, artificial intelligence, neural networks have all been used to categorize this study Figure 4.

[12] proposed SEResU-Net, an improved U-Net model that combines the Squeeze-and-Excite Network and the deep residual network. for the detection of tumors, pre-trained deep learning models such as U-Net and SE Res U-Net were used. The BraTs 2018 and 2019 datasets were used to evaluate the proposed model. As a result, when compared to other classification methods, this model achieved 93.84% sensitivity and 95.79% specificity.

A novel tumor detection algorithm with missing modalities were presented in [13]. To detect and classify brain tumors, pre-trained deep learning models Correlation models (CM), and U-Net were used. The BraTs 2018, and 2019 datasets were used to test the proposed method. In comparison to the other classification methods, this model achieved a Sensitivity of 86.8% for BraTs 2018, and 85.6% for BraTs 2019.

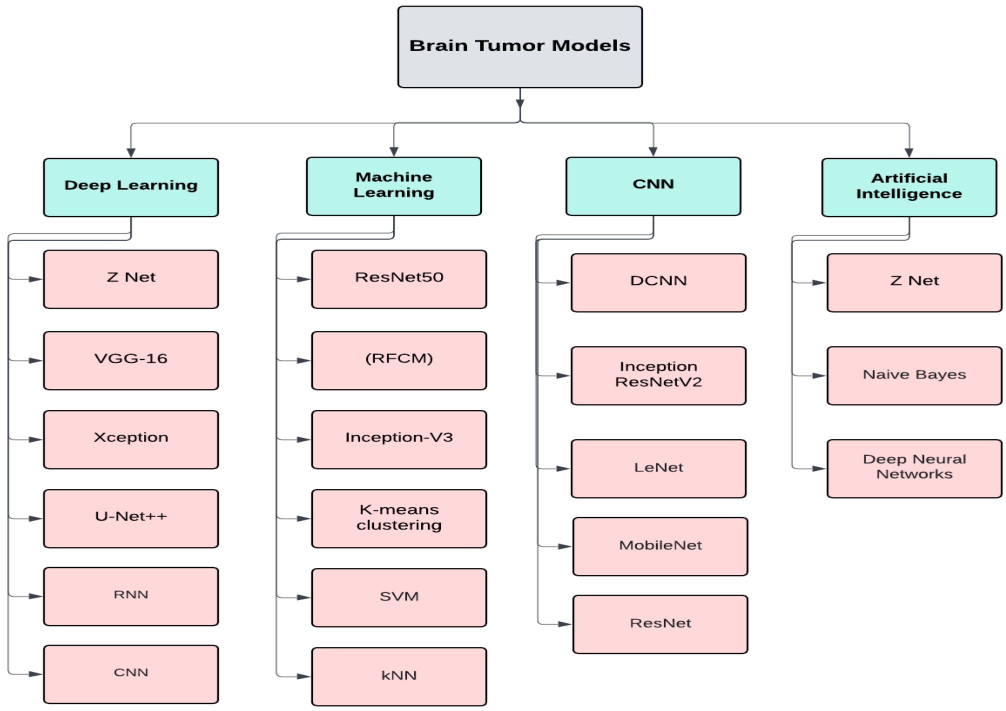

Figure 4. Classification of brain tumor models.

A deep learning algorithm for brain tumor detection and classification using different pre-trained neural network models [14]. It evaluated the model using datasets that are commonly used in the field of medical imaging. Overall, the results suggest that pre-trained neural network models are effective for brain tumor detection and classification and that the proposed model has the potential to be a useful tool for medical professionals in the field of neuroimaging. However, it is important to note that further research and testing are needed to validate the results and improve the accuracy of the models.

To detect the tumor in images, [15] introduced a deep convolutional neural network and EfficientNetB0 base model fine-tuned with our proposed layers. EfficientNet-B0, InceptionResNetV2, Xception, ResNet50, InceptionV3, and VGG16 DL models were used to detect tumors in the brain. The ImageNet dataset is applied for the test and evaluation of the proposed model. As a result, when compared to the other classification methods, this model achieved 98.87% accuracy, 99.5% sensitivity, and 99.2% specificity.

An automated segmentation method of tumors based on rough fuzzy C means and shape-based topological properties was presented in this paper [16] . Rough fuzzy C means deep learning models were used to classify the tumors. The ImageNet dataset was used to test and evaluate the proposed model. Datasets BraTS 2013, BraTS 2017. As a result, when compared to other classification methods, this model achieved 90% sensitivity and 92% specificity.

Data Augmentation and TL for the Detection of tumors in MRI were introduced in [17] . convolutional neural network (CNN) and ResNet50 DL models were used to detect the tumor in the brain. The ImageNet dataset was applied to test and evaluate the proposed model. As a result, when compared to the other classification methods, this model achieved 90% accuracy, 95% sensitivity, and 98% specificity.

[18] introduced Deep Convolutional Neural Networks (CNNs) and used both relaxation and restriction methods in the CNN model from numerous perspectives to guide and uphold the model to maintain a balance of global morphological features and local spatial information in this multi-modal. CNN Deep Net classifier pre-trained dl models were used to detect brain tumors. The BRATS 2019 dataset was used to test the proposed model. Consequently, when compared to the other classification methods, this model achieved a sensitivity of 90.3% and a specificity of 92.9%.

A deep Learning method that provides a way for efficiently detecting Tumors using modified fuzzy C means clustering [19]. To classify the tumors, deep learning models such as modified fuzzy C means, clustering and grey wolf optimizer were used. The datasets BraTS 2015, 2017, and 2018 were applied to test and evaluate the proposed model. As a result, when compared to the other classification methods, this model achieved Accuracy of 98.32%, 96.97%, and 92.67% for Modified Fuzzy C Means, Clustering (MFCM), and GWO (Grey Wolf Optimizer). The scored specificity is 80.7% and the sensitivity is 80.5%.

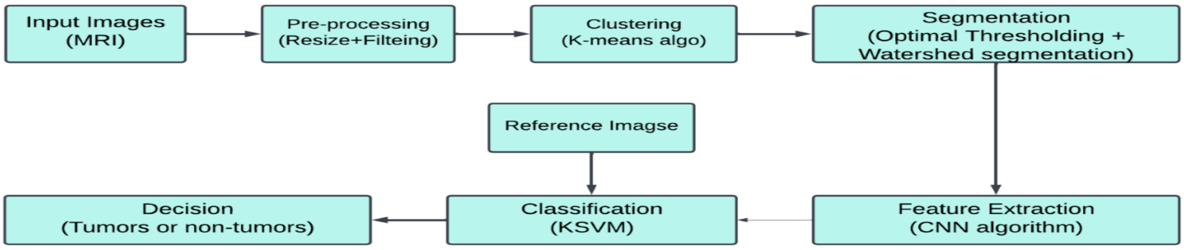

Figure 5. Flow chart for the detection of brain tumors using CNN models.

A CNN structure for the robotic detection of tumors in magnetic resonance imaging images was presented in [20] . Deep convolutional neural network pre-trained DL models were applied to categorize brain tumors Figure 5. The ImageNet dataset was used to verify and assess the proposed model. As a result, when contrasted to other classification methods, this model achieved 99% accuracy, 96.12% sensitivity, and 99.65% specificity.

A supervised convolutional deep net classifier for the identification, and treatment of tumors using a DL technique [21]. This method classifies the detected tumor image as either benign or malignant. CNN Deep Net classifier pre-trained deep learning models were used to detect the tumor. The open-access data set was used to evaluate the proposed model. BRATS dataset is freely available. In comparison to the other classification techniques, this model achieved 99.4% accuracy, 97.2% sensitivity, and 98.6% specificity.

An adaptation of the architecture of U-Net++ that is lightweight and comparable to the performance of previous work evaluated on the same data [22]. Evaluation of the tumor capabilities of the model, which is an adaptation of U-Net. Using the BraTs 2019 dataset, U-Net++ is the most used ML classification algorithm. As a result, when compared to other classification methods, this model achieved 86.71% sensitivity and 99.44% specificity.

Several DL models were analyzed and compared to determine the best performing model for detecting brain tumors from MR images [23]. They used a freely available MRI dataset to test and evaluate the performance of each model. It is important to note that the results of this study may not be generalizable to other datasets or real-world scenarios, and the selection of the best model will depend on the specific requirements and constraints of the problem at hand. Nonetheless, the study provides valuable insights into the performance of different deep learning models for brain tumor detection from MR images.

A popular deep learning architecture that was used to create a brain tumor diagnostic system [24]. Three different optimization algorithms are used to train and test deep transfer learning models on a brain MRI dataset (ADAM, SGD, and RMS prop). Xception, a pre-trained DL model, was used to detect tumors. The open dataset was used for the testing and evaluation of the proposed model. As a result, when compared to other classification methods, this model achieved 99.67% accuracy, 99.68% sensitivity, and 99.66% specificity.

A comprehensive review of proposed techniques of brain cancer detection along with sources, performance evaluation and datasets are presented in Table 1.

Table 1. Sources, performance evaluation and datasets used by proposed techniques for brain tumor detection.

Year/ Publisher	Performance Evaluation			Ref. No	Data Set	Model/ Technique
	Accuracy	Sensitivity	Specificity			
2022 (IEEE)	High	×	×	[25]	TCGA – LGG	Z Net

2022 (IJAER)	High	×	×	[14]	Kaggle depository website ImageNet BraTS 2017, BraTS 2018	VGG16 ResNet50 Mobile Net InceptionV3
2022 (Neuroscience Informatics)	High	Medium	Medium	[19]	BraTS 2015 BraTS 2017 BraTS 2018	Modified Fuzzy C Means Clustering (MFCM). GWO (Grey Wolf Optimizer)
2022 (IEEE)	High	×	×	[23]	Kaggle	VGG-16, VGG-19, ResNet50, Inception ResNetV2, InceptionV3, Xception, DenseNet20
2022 (IEEE)	High	High	High	[24]	brain's MRI	Xception
2022 (IEEE)	×	Medium	High	[26]	BraTS 2017, BraTS 2018	Hybrid-DANet (HWADA) (MCS) (RM)
2021 (IEEE)	×	Medium	×	[13]	BraTS 2018 BraTS 2019	Correlation model. (CM) U-Net
2022 (IEEE)	High	High	High	[15]	ImageNet	EfficientNet-B0 VGG16, InceptionV3, Xception, ResNet50, InceptionResNetV2
2022 (IEEE)	High	×	×	[27]	Regions of Interest (ROI)	Cumulative Variance method (CVM)
2021 (IEEE)	×	Medium	High	[22]	BraTS 2019	U-Net++
2022 (IEEE)	×	High	High	[15]	BraTS 2018 BraTS 2019	U-Net SE Res U-Net
2022 (IEEE)	High	×	×	[27]	Regions of Interest (ROI)	Cumulative Variance method (CVM)

2021 (Springer)	×	High	High	[16]	BraTS 2013 BraTS 2017	Rough fuzzy C-means (RFCM)
2021 (IEEE)	High	Medium	High	[28]	IBSR and MS-free dataset BRATS 2013	Laplacian lion optimization algorithm (LXLOA)
2021 (IEEE)	×	×	×	[29]	Open source	K-means clustering algorithm
2022 (IEEE)	×	×	×	[30]	BraTS 2018 BraTS 2020	U-NET
2022 (IEEE)	High	High	High	[17]	ImageNet	CONVOLUTIONAL NEURAL NETWORK (CNN) ResNet50
2022 (IEEE)	High	×	×	[31]	BraTS 2012	ResNet-50 VGG-16 Inception-V3 CNN
2022 (Elsevier)	×	High	High	[18]	BRATS 2019	Deep Convolutional Neural Networks (CNNs)
2021 (IEEE)	High	×	×	[32]	MSD BraTS 2021	Swin UNEt TRansformers
2022 (IEEE)	High	High	High	[20]	ImageNet	Deep Convolutional Neural Network (DCNN)
2022 (Signal, Image & Video Processing)	High	High	High	[33]	BraTS benchmark	multi-level attention network (MANet)
2022 (BioMed Research International)	High	High	High	[34]	DDSM	ResNet50
2022 (ICEFEET)	High	×	×	[35]	Open source	GG16, VGG19, and Inception v3
2022 (Evolutionary Intelligence)	High	×	×	[36]	Open source	Modified Kernel with Exponential Entropy (MK2E)

2022 (Soft ting)	Compu-	High	Medium	×	[37]	Inception-v3 (CNN) model

4. Performance Evaluation/Metrics/Parameters:

As shown in Table 2, multiple metrics, such as F1-score, precision, recall, and accuracy can be used to determine the effectiveness of various classifiers for disease prediction. As shown in Table 3, the terms true negative, true positive, false negative, and false positive are used to describe classification accuracy, which is related to sensitivity and specificity.

Table 2. Statistics for assessing the categorized models.

Metrics	Formula	Evaluation Focus
Sensitivity	(TP)/(TP+FN)	The network's potential to identify the actual tumor images.
Specificity	(TN)/(TN+FP)	A network's potential to correctly identify the actual non-tumor images.
Accuracy	(TP+TN)/(TP+TN+FP+FN)	A network's potential to identify the classes of tumor, such as +ve or -ve.
Error rate	(FP+FN)/(TP+FP+TN+FN)	Misclassification defect is measured by dividing the number of wrong predictions by the total number of evaluated instances.
Precision	(TP)/(FP+TP)	Precision is used to calculate the percentage of accurately predicted +ve patterns in a positive class.
Recall	(TP)/(TN+TP)	The portion of identified +ve patterns is determined by recall.
Likelihood	(sensitivity)/(1-specificity)	The likelihood ratio is the difference between these probabilities.

TP: The positive samples were identified as positive.
FN: The +ve but classified as negative samples.
FP: The –ve samples that are labeled as positive.
TN: The samples that are classified as negative.

A confusion table is a situational table in which the columns show the predicted class, and the rows represent the true class. Explain each component of the confusion matrix now.

Table 3. Table of Confusion

Actual	+ve prediction	-ve prediction
+ve	TP	FN
-ve	FP	TN

Several parameters, such as recall, specificity, precision, accuracy, and sensitivity, are used to measure the effectiveness of classification techniques for disease prediction. The model that falls between the 90% and 99% ranges will perform well Figure 6. The model with a score between 80% and 89% will have an intermediate performance. The model with a score between 70% and 79% will perform poorly.

Caffe, MXNet, Tensorflow, MatConvNet, Torch, and Theano are some of the most popular software frameworks in recent years shown in Table 5. Caffe is a Convolutional Architecture for Fast Feature Embedding . MXNet, which stands for "Mix and Maximize Networks," is a rising deep learning library that makes many system-level design decisions. Tensorflow, named after the procedures, that such neural networks perform on massive data arrays known as "tensors," and "MATLAB Convolution Networks"

(MatConvNet) are two significant frameworks. Torch and Theano are currently the least used deep learning tools. Table 5 summarizes a comparison study for popular DNN frameworks.

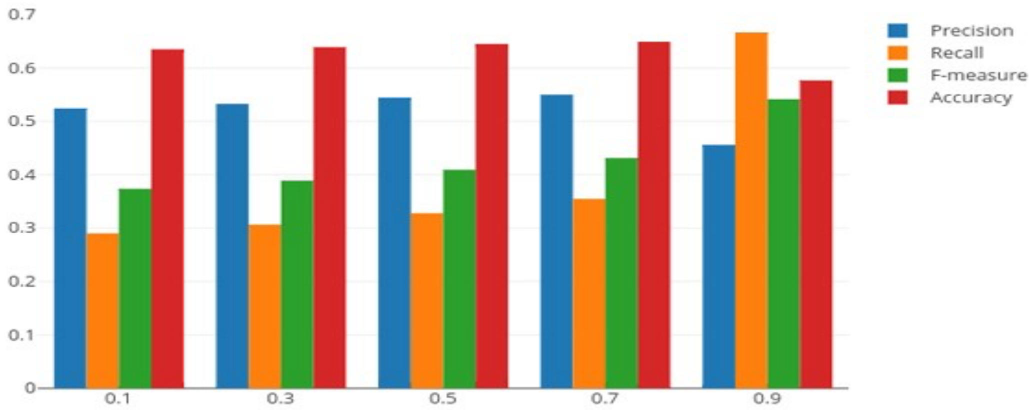

Figure 6. Relationship between accuracy, precision recall.

Table 4. A Comparison of Popular Deep Neural Network Frameworks

Framework	Language	Advantages
Caffe	C++	• Open-source framework • C++ and CUDA implementation • Python support • Image processing expertise • Fast performance: practices approximately 1000 images/sec (intimation) and 250 images/sec (learning)
MXNet	C++	• Open-source framework • C++ and Python support • CPU and GPU modes and multi-GPU support • Computer vision and machine vision applications supported • Efficient in building larger networks • Run productive time
MatConvNet	MATLAB	• Supports MATLAB language • Supports C++ • Versatile • Simple to apply
Torch	C and Lua	• Rapidly running and good dimensional stability • Many pre-trained models • Run on GPU • Used by Facebook and Twitter
Theano	Python	• CPU and GPU modes • Supports Python • Very customizable and versatile • Great encouragement for RNN
Tensorflow	C++ and Python	• Open-source platform • Supports C++ and Python • CPU and GPU modes and multi-GPU support • Runs on Android and iOS • Extremely versatile and adaptable.

	• Caffe converter support • The official Google DL framework

5. Conclusions

This work presents the categorization of detecting and segmenting brain tumors as well as highlighting and contrasting some of the essential features of cutting-edge techniques applied to this field. Among the most popular techniques are machine learning techniques like fuzzy K-means clustering and random forests, as well as the widespread use of the CNN method. Specifically, literature used the convolutional neural network method to reach the best performance. Overall, we categorize the research work in the area and compare it to other recent investigations. One issue is that large publicly available datasets are necessary for deep learning algorithms' training, and their absence is a barrier. To support upcoming research in this area, there is still a comprehensive room to enhance the quantity of datasets available and to improve access to them. Classify imbalances in the various tumor kinds are another frequent problem. By rotating or shrinking existing photos, data augmentation techniques are frequently used to address this issue. Most deep learning techniques used today classify tumor regions, however, the network is unaware of the anatomical location of the tumor region. The goal of future study in this area can be to include datasets into the neural networks, perhaps by inputting the network to the complete image. However, due to memory and computing resource limitations, training the network on images of brain tumors is not viable due to their typical high resolution and gigapixel size.

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